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► To cite this version:

D. Bensaad, A. Soualhi, F. Guillet. A new leaky piston identification method in an axial piston pump based on the extended Kalman filter. *Measurement - Journal of the International Measurement Confederation (IMEKO)*, 2019, 148, pp.106921 -. 10.1016/j.measurement.2019.106921 . hal-03487768

HAL Id: hal-03487768

<https://hal.science/hal-03487768>

Submitted on 20 Dec 2021

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A new leaky piston identification method in an axial piston pump based on the extended Kalman filter

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Abstract

Volumetric losses are essential to ensure proper lubrication of moving components in an axial piston pump (APP). However, amplification of these volumetric losses can be observed when one or more pistons of the APP degrade due to friction and contaminated fluid. This amplification of volumetric losses due to a worn piston is often called a piston leak. The latter disturbs the output pressure signal and considerably reduces the efficiency of the pump. It also generates significant vibrations that can lead to the resonance of the pump structure. In this context, it is necessary to implement a diagnosis tool to identify the worn piston among the others. This will allow effective maintenance interventions by changing only the worn piston instead of all pistons.

This paper presents a new approach based on the physical model of the pump to identify the worn piston from the healthy ones. It begins by modelling the dynamic comportment of the pump in a nonlinear state model. Then, the extended Kalman filter (EKF) is adapted to estimate pressure in piston chambers. This estimation gives the possibility to observe the pressure into each piston chamber and then allows the identification of the worn piston. The proposed approach is validated on an APP test rig. The obtained results prove the efficiency of the proposed approach in identifying the worn piston.

Key words: Axial piston pump; piston leak; extended kalman filter; fault diagnosis

1 Introduction

The axial piston pump (APP) is a fundamental component in power hydraulic systems. Compared to other hydrostatic pumps, APP presents more advantages especially in high pressure operating conditions. Indeed, it offers the best efficiency due to its cylindrical displacement chambers that does not require complicated seals. Unfortunately, working under high pressure makes the APP subject to the apparition of faults causing efficiency decrease and ultimately total breakdown. Hence, implementing efficient detection and diagnosis techniques is essential to improve pump reliability and save important maintenance costs.

Different types of fault can occur on an APP; among them we can find cavitation [1], piston crack [2, 3], bearing faults [4], variable mechanism fault [5], rotor wear [6], abrasion of valve plate [7], abrasion of slipper [8, 9, 10], loose slipper fault [11]. The occurrence of each type of fault depends on the application and the design of the pump. However, one important aspect of fault did not receive enough attention from researchers, namely internal leakages. Indeed, most of the studies carried out on this topic concern the mathematical modelling of leakages [12, 13] while fewer works were addressed to the problem of internal leakages diagnosis [14, 15, 16]. The present paper focuses on the diagnosis of one type of internal leakages, namely piston leak.

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Piston leak occurs between two components of the pump: the piston and the barrel. It is the result of friction forces applied on the piston cylindrical surface and the cylinder bore surface [17]. The degradation of these two surfaces increase the clearance between them and creates more leakage flow. This phenomenon can be accelerated and localized on a single piston when the fluid is contaminated with debris. Indeed, APP installations do not contain suction filtration, which allows sometimes the debris contained in the tank to pass through the pump. This passage of debris accelerates the surface degradation creating important piston leaks. Figure 1 explains this degradation process. The consequence of a piston leak is a decrease in the pump's efficiency as well as an increase in the pump structure vibration.

In term of measured signal, the leakage introduces a periodic drop in the output pressure signal of the pump. Conventional signal-based diagnosis methods are able to detect the presence of a piston leak [14, 15]. For instance, a simple spectral analysis shows an increase in the amplitude of the rotation frequency. However, these methods are unable to identify the leaky piston among the good ones. To overcome this limitation, a new model-based diagnosis approach is proposed to identify the leaky piston. Based on the proposed approach, an effective maintenance intervention is possible by changing only the worn piston.

Fault diagnosis techniques can be classified into three main categories depending on the approach nature [18]. Hence, we find signal-based, model-based and knowledge-based approaches' [19]. In this paper, we focus on model-based approach for two reasons. It offers a good physical understanding of the fault occurrence and requires small amounts of data. The basic principle of model-based diagnosis approach is to compare between the measured system outputs and the predicted ones [18]. This comparison generates residuals used to make the diagnosis decision. The Kalman filter is one among the most used tools in model-based fault diagnosis techniques [20]. Originally formulated for linear systems [21], its use became more common with its extension to nonlinear systems, the extended Kalman filter (EKF). Usually, linear form is limited in describing the dynamics of a physical system. This is the case of axial piston pump which is commonly modeled by nonlinear equations. In the present paper, the EKF is adapted to identify the leaky piston in an APP by considering cylinder bores pressures and the pump output pressure as state variables. Then, a residual signal is calculated from the pressure estimates to make the diagnosis decision.

The rest of this article is organized into 5 sections. Section 2 presents the mathematical modelling of an APP by both algebraic and differential equations. The modelling of different types of internal leakages is also given in order to achieve simulation of leakage faults. Section 3 recalls fundamental equations of the EKF and details the proposed implementation of it as a leak detector filter. Section 4 describes the HYDAC APP test bench used

Figure 1: Degradation of the piston surface in presence of debris.

to perform experimental tests. Section 5 presents the methodology and results of the leaky piston identification method. Finally, a conclusion is presented in Section 6.

2 Mathematical modelling

In a model-based diagnosis approach, the model must represent the system under investigation [18]. Therefore, the following model reflects the experimental test bench presented in section 4 and its hydraulic circuit presented in figure 2. According to [13], an APP can be modeled by the following equations:

$$\frac{dP_i}{dt} = \frac{B}{V_i}(Q_{g,i} + Q_{in,i} - Q_{d,i} - Q_{l,i}) \quad (1)$$

$$V_i = V_0 - A_p \cdot R \cdot \tan(\beta)(1 - \cos(\varphi_i)) \quad (2)$$

$$Q_{g,i} = -\frac{dV_i}{dt} = A_p \cdot R \cdot \omega \cdot \tan(\beta) \cdot \sin(\varphi_i) \quad (3)$$

$$Q_{d,i} = A_{d,i} \cdot C_d \cdot \sqrt{\frac{2|P_i - P_d|}{\rho}} \cdot \text{sgn}(P_i - P_d) \quad (4)$$

$$Q_{in,i} = A_{in,i} \cdot C_d \cdot \sqrt{\frac{2|P_{in} - P_i|}{\rho}} \cdot \text{sgn}(P_{in} - P_i) \quad (5)$$

where:

- P_i , P_d and P_{in} are respectively the instantaneous pressure in the i th piston chamber, the discharge chamber pressure and the intake chamber pressure;
- V_i is the volume in the i th piston chamber and V_0 is the initial volume of the piston chamber when the piston is at the bottom dead center (BDC) position. The latter corresponds to the farthest piston position from the valve plate (see figure 3);
- $Q_{g,i}$, $Q_{d,i}$, $Q_{in,i}$ and $Q_{l,i}$ are respectively the geometry flow created by the i th piston motion, the discharge flow that goes from the i th piston chamber to the discharge chamber, the intake flow that goes from the intake chamber to the i th piston chamber and the total leakage flow of the i th piston;
- A_p , $A_{d,i}$ and $A_{in,i}$ are respectively the piston cross-section area, the intake area and the discharge area of the i th piston. The area A_d and A_{in} result from the passage of the cylinder port through the suction port and the discharge port of the valve plate;
- The parameters B , C_d and ρ define the characteristics of the fluid. They represent respectively the fluid bulk modulus, the discharge coefficient and the fluid density;
- R , β , φ_i and ω define respectively the piston pitch radius, the inclination angle of the swash plate, the angular position of the piston and the angular velocity of the drive shaft. The last two parameters depend on each other by the relation $\varphi_i = \omega t - (i - 1)\alpha$ in which α is the piston offset angle, i is the piston number and t is the time instant;
- $|\cdot|$ stands for the absolute value symbol and $\text{sgn}(\cdot)$ for the sign symbol. For a real number x , $\text{sgn}(x) = -1$ if $x < 0$, $\text{sgn}(x) = 0$ if $x = 0$ and $\text{sgn}(x) = 1$ if $x > 0$.

Figure 2: Hydraulic circuit of the test bench.

Figure 3: Standard design of: (a) valve plate, (b) barrel.

The total leakage flow denoted by $Q_{l,i}$ in equation (1) is the sum of all internal leakages. Figure 4 shows the four different leakages that can be found in our APP: leakage L1 between the piston and barrel, which is the focus of our work, leakage L2 between the slipper and swash plate, leakage L3 between the piston and slipper, and finally leakage L4 between the valve plate and barrel. The corresponding flow generated by these leakages are denoted respectively by Q_1 , Q_2 , Q_3 and Q_4 .

Among all leakages, L3 is the smallest because most of the fluid going through the bottom hole of the piston goes through the slipper hole making leakage L2. Hence, leakage L3 is not considered in this study. The flow generated by leakages L1, L2 and L4 can be expressed as follows:

$$Q_{1,i} = \frac{\pi \cdot d_p \cdot \delta_p^3}{12 \cdot \mu \cdot l_k} (P_i - P_0) \quad (6)$$

$$Q_{2,i} = \frac{\pi \cdot d_h^4 \cdot \delta_s^3}{\mu (6 \cdot d_h^4 \cdot \ln(\frac{R_s}{r_s}) + 128 \cdot \delta_s^3 \cdot l_p)} (P_i - P_0) \quad (7)$$

$$Q_{4,i} = \frac{\delta_v^3}{12 \cdot \mu} \left[\frac{1}{\ln(\frac{R_2}{R_1})} + \frac{1}{\ln(\frac{R_4}{R_3})} \right] (P_i - P_0) \quad (8)$$

where:

- δ_p , δ_s and δ_v are respectively the clearance between the piston and cylinder block, the clearance between the slipper and swash plate and the clearance between the valve plate and barrel.
- d_h , R_s , r_s are respectively the diameter of the piston bottom hole, the outer and the inner radius of the slipper.
- l_p , l_k are respectively the piston length and the instantaneous gap length giving by $l_k = l_a + s_k$, where l_a is the initial gap length when the piston is at BDC and s_k is the piston displacement giving by $s_k = R \tan \beta (1 - \cos \varphi)$.
- P_0 and μ are respectively the pressure in the pump sump and the kinetic viscosity of the fluid.
- $R1$, $R2$, $R3$, $R4$ are related to the valve plate dimensions. They are shown in Figure 3.

Figure 4: Different internal leakages in an APP.

Considering the hydraulic circuit shown in Figure 2, the discharge chamber pressure can be expressed as follows:

$$\frac{dP_d}{dt} = \frac{B}{V_d} (Q_{td} - Q_v) \quad (9)$$

where $Q_{td} = \sum_{i=1}^n Q_{di}$ is the total resulting discharge flow from all the pistons, n is the number of pistons, Q_v is the flow rate through the needle valve and V_d is the discharge chamber volume. The flow rate through the needle valve Q_v can be expressed by the following equation:

$$Q_v = C_v \cdot A_v \sqrt{\frac{2(P_d - P_t)}{\rho}} \quad (10)$$

where C_v is the discharge coefficient of the needle valve, A_v is the needle valve discharge area and P_t is the tank pressure.

The diagnosis method presented in this paper is based on estimating piston chamber pressures and the output pressure of the pump. This estimation is performed with the discrete EKF. Therefore, the model described by equations from (1) to (10) is written in a discrete state-space form in the next section.

3 Pressure estimations with the EKF

The occurrence of a piston leak introduces a periodic drop in the pump output pressure signal (see figure 5). From the latter, it is not possible to directly identify the worn piston. Therefore, we propose to estimate pressures

inside each piston chamber with the EKF to capture the exact moment of full connection between the cylinder port and the discharge port of the valve plate. This moment corresponds to the pressure drop beginning which will lead us to identify the leaky piston in section 5. The EKF is chosen instead of the KF because this latter is a linear filter while the pump mathematical model is nonlinear. Therefore, the EKF is the suited filter in our case because it can deal with nonlinear systems.

Figure 5: Output pressure variation over one period in presence of a piston leak.

The general form of the EKF is given in [22] for a nonlinear system. It is described as follows:

$$\begin{cases} x_k = f(x_{k-1}, u_k, w_{k-1}) \\ z_k = h(x_k, v_k) \end{cases} \quad (11)$$

$$(12)$$

The nonlinear function f in equation (11) relates the state x_k to the previous time step state x_{k-1} , to a driving function u_k and to the zero mean process noise w_{k-1} . In equation (12), h is a nonlinear function that relates the measurement z_k to the state x_k and the measurement noise v_k . In our application, no driving function u_k is included, hence it will not be taken into consideration in further developments.

The EKF equations can be divided into two stages: the prediction stage that contains time update equations (13) and (14) and the correction stage that contains measurement update equations (15)–(17).

$$\hat{x}_k^- = f(\hat{x}_{k-1}, 0) \quad (13)$$

$$P_k^- = A_k P_{k-1} A_k^T + W_k Q_{k-1} W_k^T \quad (14)$$

$$K_k = P_k^- H_k^T (H_k P_k^- H_k^T + V_k R_k V_k^T)^{-1} \quad (15)$$

$$\hat{x}_k = \hat{x}_k^- + K_k (z_k - h(\hat{x}_k^-, 0)) \quad (16)$$

$$P_k = (I - K_k H_k) P_k^- \quad (17)$$

$\hat{x}_k^-$ and $\hat{x}_k$ are the *a priori* and *a posteriori* state estimates at step k , respectively, giving knowledge to the process and the measurement z_k . K_k is the Kalman gain. P_k^- and P_k are the *a priori* and *a posteriori* estimate error covariances. Q_k and R_k are the process noise covariance and measurement noise covariance, respectively. A_k , H_k , W_k , V_k are the Jacobian matrices of partial derivatives of f and h with respect to x , w and v . They are given

by the following equations:

$$A_{k[i,j]} = \frac{\partial f_{[i]}}{\partial x_{[j]}}(\hat{x}_{k-1}, 0), \quad W_{k[i,j]} = \frac{\partial f_{[i]}}{\partial w_{[j]}}(\hat{x}_{k-1}, 0), \quad H_{k[i,j]} = \frac{\partial h_{[i]}}{\partial x_{[j]}}(\hat{x}_k^-, 0), \quad V_{k[i,j]} = \frac{\partial h_{[i]}}{\partial v_{[j]}}(\hat{x}_k^-, 0) \quad (18)$$

In order to perform estimations of the piston chamber pressures and the output pressure, the model described by equations from (1) to (10) must be written in state-space form. Firstly, we define the following state vector $x_k = [x_1(k), \dots, x_{n+1}(k)]^T = [P_1, \dots, P_n, P_d]^T$ where P_1 to P_n correspond to pressures inside the n pistons of the pump and P_d is the output pressure of the pump. After that, we define the measurement vector as the output pressure signal of the pump, thus $z_k = [P_d]^T$. Then, for the i th piston, we express equations from (4) to (8) as follows:

$$Q_{d,i}(k) = A_{d,i}(k) \cdot C_d \cdot \sqrt{\frac{2|x_i(k) - x_{n+1}(k)|}{\rho}} \cdot \text{sgn}(x_i(k) - x_{n+1}(k)) \quad (19)$$

$$Q_{in,i}(k) = A_{in,i}(k) \cdot C_d \cdot \sqrt{\frac{2|P_{in} - x_i(k)|}{\rho}} \cdot \text{sgn}(P_{in} - x_i(k)) \quad (20)$$

$$Q_{1,i}(k) = \frac{\pi \cdot d_p \cdot \delta_p^3}{12 \cdot \mu \cdot l_k} (x_i(k) - P_0) \quad (21)$$

$$Q_{2,i}(k) = \frac{\pi \cdot d_h^4 \cdot \delta_s^3}{\mu (6 \cdot d_h^4 \cdot \ln(\frac{R_s}{r_s}) + 128 \cdot \delta_s^3 \cdot l_p)} (x_i(k) - P_0) \quad (22)$$

$$Q_{4,i}(k) = \frac{\delta_v^3}{12 \cdot \mu} \left[\frac{1}{\ln(\frac{R_2}{R_1})} + \frac{1}{\ln(\frac{R_4}{R_3})} \right] (x_i(k) - P_0) \quad (23)$$

The total leakage flow in one piston can be written as $Q_{l,i}(k) = Q_{1,i}(k) + Q_{2,i}(k) + Q_{4,i}(k)$. Finally, the nonlinear state-space model of the system can be defined by expressing equations (1) and (9) as follows:

$$\begin{cases} x_1(k+1) = \Delta t \frac{B}{V_1(k)} \left[Q_{g,1}(k) + Q_{in,1}(k) - Q_{d,1}(k) - Q_{l,1}(k) \right] + x_1(k) \\ \vdots \\ x_n(k+1) = \Delta t \frac{B}{V_n(k)} \left[Q_{g,n}(k) + Q_{in,n}(k) - Q_{d,n}(k) - Q_{l,n}(k) \right] + x_n(k) \\ x_{n+1}(k+1) = \Delta t \frac{B}{V_d} \left[\sum_{i=1}^n Q_{d,n+1}(k) - C_v \cdot A_v \sqrt{\frac{2(x_{n+1}(k) - P_t)}{\rho}} \right] + x_{n+1}(k) \end{cases} \quad (24)$$

$$z(k) = [0 \ \dots \ 0 \ 1] [x_1(k) \ \dots \ x_n(k) \ x_{n+1}(k)]^T \quad (25)$$

where Δt is the sampling time.

The nonlinear process function f is defined by the system of equations (24), which gives each state variable in step $(k+1)$ as a function of state variables in the previous step (k) . Whereas, the measurement function h is given by equation (25) which relates the measurement z_k to state vector x_k . Given the measurement z_k , for each iteration, the EKF estimates the state variables of $\hat{x}$ based on the defined state-space model of the pump, which

in this case models a healthy system. Finally, we calculate the residual signal $e = P_d - \hat{P}_d$ which is used to make the diagnosis decision. In presence of a piston leak the residual signal increases. Whereas in the healthy case, it remain insignificant. Figure 6 shows the scheme of the EKF estimator as a leak detector. The input of the EKF is the pump output pressure. Whereas the outputs are the estimated piston chamber pressures and the estimated output pressure.

Figure 6: Extended Kalman filter leak detector scheme.

4 Experimental setup

4.1 Description of the hydraulic test bench

In order to validate the proposed approach, the experimental hydraulic test bench presented in figure 7 is used. It is mainly composed of a HYDAC PPV103-10 pump driven by an electrical motor. There is also a needle valve used as a load by changing its opening. The test bench is equipped with a frequency converter. However, the motor speed was fixed at 1200 rpm for all the tests. The used oil is TELLUS S2 V32 with a density of 872 kg/m^3 and kinematic viscosity of $32 \text{ mm}^2/\text{s}$ at 40°C .

In order to acquire the instantaneous output pressure signal, a PCB113B22 piezoelectric pressure sensor with a sensitivity of 148.6 mV/MPa is used. In addition, a voltage pressure sensor IFM PU5401 is used to give DC component of the pressure signal. Moreover, a laser tachometer is placed on the drive shaft of the pump to be used as a trigger. All the signals were acquired simultaneously using an NI 9234 acquisition card. The sampling frequency is 10240 Hz and the data duration is 10 s.

Figure 7: Experimental test bench.

4. EXPERIMENTAL SETUP

4.2 Description of the HYDAC pump

The HYDAC pump is a 9 pistons APP. Its maximum displacement is equal to 10 cm^3 , which can be reached when the swash plate is at its maximum inclination. The design of this pump includes a swash plate and sliding slippers. Figure 8 shows the design details which are mainly related to the valve plate. Figure 8a and 8b show the piston-slipper assembly and the valve plate, respectively. The discharge port of the valve plate contains three openings while the suction port contains two openings, which is not a standard valve plate design. It can be noted that the valve plate contains relief notches at the edge of each port.

The mathematical model presented in section 2 must take into consideration the valve plate design because of its influence on the simulation results [23, 24]. Therefore, the discharge area A_d and the intake area A_{in} mentioned in equations (4) and (5) respectively, must be modelled according to the HYDAC valve plate design. The modelling of these two areas is performed using position relationships similarly to what is presented in [25]. The variations of A_d and A_{in} are shown in Figure 9.

Figure 8: HYDAC pump design details: (a) Piston-slipper assembly, (b) Valve plate.

Figure 9: Discharge area and intake area variations over one shaft round.

5 Results and discussion

5.1 Comparison between simulated and real output pressure signals

To ensure the proposed model presented in section 2 corresponds to the system under investigation, simulations of the output pressure signal are performed including parameters of the experimental system presented in section 4. The parameter values are given in Table 1, they include system dimensions and fluid properties. Differential and algebraic equations from (1) to (10) describing the model can be solved on Simulink by Euler solver with a fixed time step of 10^{-6} s.

Figure 10 represents simulated output pressure signals from the Simulink model and real output pressure signals acquired on the experimental test bench. In order to set all the acquired signals on the same phase, the tachometer shown in Figure 7 is used. A reflective strip is placed on the same angular position as one piston. This latter is considered as the first piston in our study. The pressure sensor is placed on the discharge chamber of the pump (see figure 7). Therefore, there is no phase delay between acquired and simulated signals. The rotational speed was fixed at 1200 rpm, thus the duration of one period is 0.05 s.

Table 1: Parameter values of the HYDAC pump model.

Symbol	value	Symbol	value	Symbol	value	Symbol	value	Symbol	value
β (rad)	0.207	$R(m)$	1.9×10^{-2}	$\omega(rad.s^{-1})$	125.66	$V_0(m^3)$	2.26×10^{-6}	d_p (m)	1.05×10^{-2}
C_d	0.6	C_v	0.6	$A_p(m^2)$	8.66×10^{-5}	$A_v(m^2)$	1.02×10^{-6}	$\rho(kg.m^{-3})$	872
$V_d(m^3)$	0.06×10^{-3}	$B(Pa)$	1×10^9	$\alpha(rad)$	0.6981	$\mu(N.s.m^{-2})$	2.7×10^{-2}	$r_k(m)$	1.95×10^{-3}
$l_k(m)$	5.9×10^{-3}	$R_s(m)$	2.59×10^{-2}	$r_s(m)$	3.65×10^{-3}	$l_p(m)$	3.45×10^{-2}	$R1(m)$	9.75×10^{-3}
$R2(m)$	1.7×10^{-2}	$R3(m)$	2.1×10^{-2}	$R4(m)$	2.85×10^{-2}	$d_h(m)$	1×10^{-3}	$P_{in}(Pa)$	1×10^5
$\delta_p(m)$	4×10^{-5}	$\delta_s(m)$	5×10^{-5}	$\delta_v(m)$	4×10^{-5}	$P_t(Pa)$	0	$P_0(Pa)$	0

Figure 10a represents output pressure signals of the pump in the healthy condition. The blue line represents the simulated pressure signal and the red dotted line represents the real pressure signal. The output pressure signal is constituted by 9 ripples for one period. These ripples are visible for both real and simulated signals. They are the contribution of the 9 pistons of the pump. Nevertheless, one ripple is not the contribution of one piston. In fact, each ripple is the contribution of several pistons at the same time. Precisely, it is the contribution of all the pistons in connection with the discharge chamber of the pump at an instant t [26]. Therefore, the presence of a leak in one piston will not affect only one ripple but several ones. In addition, it can be noted that the simulated pressure signal is constituted of 9 distinct ripples, while the real pressure signal contains small variations over one ripple. The form of these variations depends on the rotational speed and needle valve opening. They are created by the reverse flow generated when the needle valve is partially closed. More details concerning this phenomenon can be found in [27].

Figure 10b represents real and simulated output pressure signals when the first piston is leaking. The presence of the leak creates a concave drop in the output pressure signal over one round. The leak was created by removing matter from the cylindrical surface of the piston (see Figure 11). As a result, the piston diameter is reduced by $40 \mu m$. In order to generate the same fault by simulation, the parameter δ_p that represents the clearance between the piston and the cylinder bore in equation (6) become $\delta_{pl} = \delta_p + 40 \mu m = 8 \times 10^{-5} m$. By doing so, we could achieve a good match between real and simulated output pressure signals. However, the pressure drops more quickly in the simulated signal compared to the real one. Consequently, the forms of concavities of the two pressure signals are different during the dropping phase, but they are almost similar during the recovery phase.

Figure 10c represents real and simulated output pressure signals when the third piston is leaking. This leak was created by changing the position of the worn piston described previously from the first position to the third position in the barrel, with respect to the direction of rotation. The worn piston in the third position creates the

same concave drop in the pressure signal by being in the first position. Nevertheless, the drop beginning shifts from the zero reference by a certain value.

5.2 Creation of modulated output pressure signals

The real output pressure signals contain variations due to reverse flow (see figure 10). When these signals are directly used as the EKF entry, the states estimations are not good because these variations are not reproduced by the mathematical model. However, it has been shown previously that the presence of a piston leak induces a concave drop in the output pressure signal. This property can be extracted separately and added to the healthy simulated output pressure signal. Consequently, using real output pressure signal as the entry of the EKF is no longer necessary. Instead, using simulated output pressure signals containing the leak information becomes possible. For the rest of the article, we will refer inaccurately to the signals obtained by combining the simulated output pressure signals and the leak information as modulated pressure signals.

Figure 12 presents the proposed approach to create modulated pressure signals. The first step is to extract the peak envelope from the real signal. The second step is to subtract from the obtained peak envelope its maximum value. The third step is to add the peak envelope to the healthy simulated output pressure signal. The obtained signal looks like a simulated pressure signal but contains the real leak information.

Figure 13 shows a comparison between simulated pressure signals in blue lines and modulated pressure signals in red dotted lines. Figure 13a concerns the healthy pump condition. The two signals are perfectly superimposed and no difference can be distinguished. Figure 13b and figure 13c concern the presence of leak in the first and the third pistons, respectively. In the two cases, the concavities are different because the simulated pressure signals decrease more quickly than the modulated pressure signals.

Figure 10: Real and simulated output pressure signals for: (a) healthy state, (b) piston 1 leaking, (c) piston 3 leaking.

Figure 11: Healthy piston and worn piston.

Figure 12: Creation method of the modulated output pressure signal.

5.3 EKF adjustment

After obtaining the modulated output pressure signals which are used as the EKF input, we must adjust the parameters of the EKF leak detector according to our system. Firstly, the Jacobians defined in equation (18) are calculated from the process function f and the measurement function h . The matrix A_k is obtained by Matlab function *jacobian* and the matrix H_k is given by $H_k = [0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 1]$. Secondly, assuming that process and measurement noises are white, Gaussian and stationary, the covariance matrices Q_k and R_k are constants. Assuming also that state variables of the system are independent from each other, then Q_k and R_k are diagonals. Finally, it can be deduced that the Jacobian matrices related to noises W_k and V_k are unity matrices.

In order to initialize the EKF, we must determine the initial values of the state vector $\hat{x}_0$, the initial estimation error covariance P_0 , process noise covariance Q_k , and the measurement noise covariance R_k . The values of the state estimates are set to zero except for the state estimate of the output pressure which is set to a sufficiently high value, equal to 10^5 . The latter corresponds to the intake pressure value, thus $\hat{x}_0 = [0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 10^5]$. The initial estimation error covariance P_0 is set to be a diagonal matrix where all the diagonal values are equal to 10^2 . Otherwise, the matrices Q_k and R_k are considered to be constant as it was specified earlier and will be

noted Q and R , respectively. In fact, R contains only one component related to the noise of the output pressure measurement. Hence, R is given as $R = [10]$ considering the piezoelectric signals are not noisy. Whereas Q is a diagonal matrix of 10×10 . Each component of the diagonal corresponds to one state variable. It was decided to set all the diagonal components of the matrix Q to 10^{-9} which means we have extremely high confidence in the process modelling.

5.4 Results of the EKF estimation

The modulated pressure signals showed in figure 13 are used to achieve estimation with the EKF. The estimation results are shown in figure 14. The black lines represent the residual signal, the red lines represent the estimated pressure inside the first piston and the green dotted lines represent the estimated pressure inside the third piston. Each plot has two y axes, the right one concerns the estimated pressures and the left one concerns the residual signal. The latter is the difference between a modulated output pressure signal and an estimated one. Only pressures inside pistons one and three are shown because they are concerned by the leak tests. The variation of the pressure inside the piston is composed of two parts as it was explained in [28]. The first one concerns the aspiration phase and the second one concerns the discharge phase.

Figures 14a, 14b and 14c were obtained by using the modulated signals shown in red dotted lines in figures 13a, 13b and 13c as the EKF entry. In the healthy condition, figure 14a, no change is noticeable in the residual signal. While in presence of leak in the first piston, figure 14b, we note an increase in the residual signal when the first piston is completely connected to the discharge chamber. This event happens at the instant shown by the black dotted line in figure 14b. It corresponds to the instant when the entire surface of the cylinder port is connected to the discharge port of the valve plate. Similarly, in presence of leak in the third piston, figure 14c, we note an increase in the residual signal when the third piston is completely connected to the discharge chamber. Finally, it can be concluded that the residual signal increases when the leaky piston is fully connected to the discharge chamber of the pump, offering an efficient method to identify the leaky piston.

Figure 13: Modulated and simulated output pressure signals for: (a) healthy state, (b) piston 1 leaking, (c) piston 3 leaking.

5.5 Diagnosis decision

The last step in a model-based fault diagnosis technique is the decision making using the generated residual signal. This decision can be done using a constant threshold or an adaptive one [20]. In our case, two thresholds are defined in order to implement the diagnosis decision algorithm. They represent respectively 1% and 10%

Figure 14: Residual signal and estimations pressure inside piston 1 and 3 for: (a) healthy state, (b) piston 1 leaking, (c) piston 3 leaking.

from the peak to peak value of the healthy output pressure signal. The peak to peak value is used because of its sensitivity to the presence of a piston leak. Indeed, the drop caused by a piston leak in the output pressure signal leads to an increase in the peak to peak value. Furthermore, we define t_0 as the piston 1 full contact instant and T as the signal period (see figure 15). The diagnosis decision algorithm is presented in algorithm 1.

Figure 15: Residual signal in presence of leak in piston 1.

Algorithm 1

```

1:  $t = [t_0 : \frac{T}{9} : T]$ 
2: for  $i = 1 : 9$  do
3:   if  $i \neq 9$  then
4:     if  $\text{Residual}(t(i)) < \text{threshold1}$  and  $\text{Residual}(t(i+1)) > \text{threshold2}$  then
5:        $\text{pos} \leftarrow \text{position}(t(i))$ 
6:       return fault in piston (pos)
7:     else
8:       return No fault
9:     end if
10:  else
11:    if  $\text{Residual}(t(i)) < \text{threshold1}$  and  $\text{Residual}(t(i-8)) > \text{threshold2}$  then
12:       $\text{pos} \leftarrow \text{position}(t(i))$ 
13:      return fault in piston (pos)
14:    else
15:      return No fault
16:    end if
17:  end if
18: end for

```

5.6 Case of simultaneous piston leaks

In the previous sections, we have presented the effect of one piston leak on the output pressure signal, but what happens if more than one piston are leaking simultaneously? To answer this question we have conducted an experimentation using three worn pistons with different severities. We have chosen different worn severities to reflect the randomness of piston leaks occurrence. These severities are giving by $\delta_{pl1} = \delta_p + 40 \mu m = 8 \times 10^{-5} m$, $\delta_{pl2} = \delta_p + 20 \mu m = 6 \times 10^{-5} m$, $\delta_{pl3} = \delta_p + 5 \mu m = 4.5 \times 10^{-5} m$. Figure 16 shows the disposition of the 3 worn pistons in the barrel. The first position in figure 16 refers to the first piston position with respect to the trigger.

In order to demonstrate the universality of the proposed method, we have changed the operating conditions

of the first experiment. Indeed, the rotation speed has become 1450 rpm (1200 rpm in the first experiment) and the load is changed so that the average pressure is around 137 bar (around 160 bar in the first experiment).

Figure 17 shows the obtained pressure signals when three pistons are leaking simultaneously. Figure 17a shows the obtained pressure signal when the big wear piston δ_{pl1} is in the first position (see figure 16), the medium wear piston δ_{pl2} is in the fourth position with respect to the direction of rotation and the small wear piston δ_{pl3} is in the seventh position. At first sight, we note a concave drop similar to the one introduced by one piston leak (see figure 10). The same remark can be made for figure 17b where piston δ_{pl1} is in the fourth position, piston δ_{pl2} is in seventh position and piston δ_{pl3} is in the first position.

Figure 16: Disposition of the worn pistons in the barrel.

Figure 17: Real and simulated output pressure signals for: (a) big wear piston in the first position, (b) big wear piston in the fourth position.

Figure 18 shows the residual signal and estimated pressures inside piston 1 and 4. Figure 18a concerns the case of piston δ_{pl1} in the first position. It can be seen that the residual signal begins to increase when piston δ_{pl1} is in full contact with the valve plate. We can note also the presence of deformations in the residual signal that wasn't noticeable in the one piston leak case. These deformations are introduced by the medium wear δ_{pl2} and the small wears δ_{pl3} . The same remark can be made for figure 18a where we see an increase in the residual signal when piston δ_{pl1} is in full contact with the valve plate.

Based on the residual signal and the contact instants of all pistons, it's possible to identify the big wear piston δ_{pl1} using algorithm 1. However, the identification of the two remaining worn pistons is more complicated

because the decision criterion is not obvious. We can conclude that the proposed method is able to identify the piston with the largest defect when there is a multitude of pistons leaking simultaneously.

Figure 18: Residual signal and estimations of pressure inside piston 1 and 4 for: (a) big wear piston in the first position, (b) big wear piston in the fourth position.

6 Conclusion

This paper presents a new model-based fault diagnosis method able to identify the leaky piston in an APP. This method implies mathematical modelling of the system under investigation. Therefore, a mathematical model of an APP is presented and implemented on Simulink. Otherwise, An experimental test bench is used to perform leakage tests. Output pressure signals are acquired in the healthy condition and in presence of piston leaks. Simulated output pressure signals are compared with real output pressure signals for different health states to showcase the model's robustness.

The EKF was adapted in order to identify the leaky piston among the good ones. Firstly, the EKF is used to estimate piston chamber pressures and the output pressure of the pump. Then, a residual signal is calculated using the EKF inputs and outputs. Finally, the residual signal is used along with estimated piston chamber pressures to make the diagnosis decision. The presented results show the efficiency of the proposed approach.

In the case of simultaneous piston leaks with different severities, the proposed method is able to identify the piston with the largest defect, offering the possibility of replacing it and therefore preserving the installation from significant damage.

Acknowledgments

The authors would like to thank Bpifrance for the financial support.

Appendix A Nomenclature

n	Number of pistons
β	Inclination angle of the swash plate (rad)
φ	Angular position of the piston (rad)
R	Piston pitch radius (m)
ω	Angular velocity of the drive shaft ($rad.s^{-1}$)
d_p	Piston diameter (m)
C_d	Discharge coefficient of the cylinder port
C_v	Discharge coefficient of the needle valve
A_p	Piston cross-section area (m^2)
A_v	Discharge area of the needle valve (m^2)
A_{in}	Intake area of the valve plate (m^2)
A_d	Discharge area of the valve plate (m^2)
ρ	Oil density ($kg.m^{-3}$)
V_d	Discharge chamber volume (m^3)
V_i	Instantaneous volume of the piston (m^3)
V_0	Initial volume of piston chamber when piston is at BDC (m^3)
B	Oil bulk modulus (Pa)
α	Piston offset angle (rad)
μ	Oil dynamic viscosity ($N.s.m^{-2}$)
r_k	Width radius of the cylinder port (m)
l_k	Length of the linearised cylinder port (m)
R_s	Slipper outer radius (m)
r_s	Slipper inner radius (m)
l_p	Piston length (m)
$R1, R2, R3, R4$	Parameters of the valve plate (m)
d_h	Diameter of the piston bore (m)
P_{in}	Pressure in the intake port of the valve plate (Pa)
P_d	Pressure in the discharge port of the valve plate (Pa)
δ_p	Distance between a piston and a cylinder chamber (m)
δ_{pl}	Distance between a piston and a cylinder chamber in the presence of a piston leak (m)
δ_s	Distance between the slipper and the swash plate (m)
δ_v	Distance between the valve plate and the cylinder block (m)
P_t	Tank pressure (Pa)
P_0	Pressure in the pump sump (Pa)
P_i	Pressure inside the i^{th} piston (Pa)
Q_g	Geometry flow of the piston ($m^3.s^{-1}$)
Q_d	Discharge flow of the piston ($m^3.s^{-1}$)
Q_{in}	Intake flow of the piston ($m^3.s^{-1}$)
Q_l	Total leakage flow ($m^3.s^{-1}$)
l_k	Piston gap length (m)
s_k	Piston displacement (m)

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