DETECTION OF HYDRAULIC CYLINDER LEAKAGE

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Abstract:
This Thesis investigates the application of Fault Detection and Diagnosis (FDD). Experiments were performed on the hydraulic crane setup at the Hydraulics Laboratory at the AAU Esbjerg Campus. Hydraulic and mechanical models of the system in question were obtained. Simulated and experimental data were compared and mathematical non-linear model was validated. System modeling and validation is done for the non-faulty system, later introduced with the faults, i.e. internal and external leakage. Since the main objective of the Thesis is to detect said faults, Extended Kalman Filter (EKF) is applied in a form of State Augmented Extended Kalman Filter (SAEKF). Leakage coefficients are chosen for augmented states. Performance of the chosen method is investigated and discussed.

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Preface

This Long Thesis was made by the Offshore Energy Systems Master programme student at the Aalborg University, Esbjerg as a $9^{th}$ Semester Project and $10^{th}$ Semester Thesis in one.

I would like to thank my supervisor Jesper Liniger for his supervision throughout the entire process and for always having patience and time to help.

I would also like to thank my beautiful family for constant support and encouragement.

Lastly, to Irena, for all the love.

Aalborg University, May 31, 2019

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Chapter 1

Introduction

1.1 Initiating problem

Wind turbines are currently designed for a 25-year service life with the possibility of operational extension. Extending their efficient operation can significantly increase the return on investment and decrease the cost of electricity [1].

Hydraulic systems play a great role in modern industry, such as offshore wind energy systems design. Recent years yielded in rapid growth of large wind turbines development, thus increasing the impact on both safety and cost. Need for reliable systems is therefore essential.

Reliability is described as the probability of a component or system to function correctly over a certain period of time and for certain operating conditions [2]. To ensure the system is reliable and to minimize the possibility of a fault occurrence, systematic approach needs to be taken during the system design process. This is done by identification procedures such as Failure Mode Effect Analysis (FMEA) or Fault Tree Analysis (FTA) [1].

Fault Tree Analysis (FTA) uses a top-down approach where the system is broken down into subsystems and components and connected using logic gates in order to cover entire range of scenarios where a fault can occur and paths of the fault propagation.
Figure above is showing certain causes and consequences of a cylinder leakage. Except possible component damage, leakage can also lead to hydraulic system malfunction and even emergency shut down. This means longer down-time and increase in maintenance cost and time. More serious scenarios implicate health and safety issues or even fatalities. Early leakage fault detection decreases said events while increases system reliability.

### 1.2 Problem decomposition

The goal of this project is to perform a Fault Detection and Diagnosis method called Extended Kalman Filter on an experimental hydraulic crane setup in order to detect level of cylinder leakage. This is done by augmenting the state-space model with leakage coefficients as new states.

In order to achieve set goal, the initiating problem needs to be decomposed into the following segments:

- Obtaining the hydraulic and mechanical model and building the simulation of the hydraulic crane process
- Validating model accuracy by comparing experiment and simulation data
1.2. Problem decomposition

- Extended Kalman Filter application on the hydraulic crane model and augmenting the state-space model
- Validating the method used

As detecting cylinder leakage being the main focus of the project, three different leakages are regarded:

- Internal cylinder leakage
- External leakage from piston side control volume
- External leakage from rod side control volume
Chapter 2

System Modeling

2.1 Hydraulic crane setup

System in question is a hydraulic crane, an experimental setup located in the Fluid Power Laboratory at the Aalborg University Esbjerg. The crane works on the pantograph principle with a hydraulic cylinder as the force actuator.

A pantograph is a mechanical device originally made for scaled drawing. User is drawing while simultaneously copying the image in a larger or a smaller scale.
2.2. Hydraulic modeling

(Figure 2.2). Based on the principle of two pairs of parallel lines intersecting, corresponding angles and length ratios are preserved. Therefore, as the piston in the cylinder is extended/compressed, the crane end movement trajectory is proportionately enlarged.

Figure 2.2: Pantograph [3]

In the sections below it will be described how the mathematical model is obtained by deriving and combining mechanical and hydraulic modeling.

## 2.2 Hydraulic modeling

Most of the hydraulic machines in use today operate hydrostatically – that is through pressure. In a hydrostatic device, power is transmitted by pushing on a confined liquid. A transfer of energy takes place because a quantity of liquid is subject to pressure [4].

The main components of the hydraulic crane system are:

- fluid (hydraulic oil) acting as a power transmitter, lubrication for the moving parts and protection against corrosion.
- crane accumulator which contains oil and enables the circular flow (both start and end point in the circuit); also regulates the fluid temperature since not always the same fluid is in motion.
- hydraulic pump sets the fluid in motion from the tank.
- piston inside of the hydraulic cylinder which is displaced based on the fluid inflow in a certain chamber.
- filters needed to purify the oil from potential debris and fragments. Filters may be inserted in suction lines (to protect the pump), delivery lines (to protect valves and actuators) and return lines (to remove picked up contamination) [4].
2.2. Hydraulic modeling

- Directional Control Valve controls the amount and direction of the fluid in the system which indirectly controls the crane movement velocity.

### 2.2.1 Directional Control Valve (DCV)

Directional control valves belong to the group of valves controlling flow direction. Their purpose is to direct pump flow to an actuator as well as allow return flow from the same actuator to the reservoir. They are classified according to the number of service ports and number of possible configurations (positions).

![Figure 2.3: Schematic drawings of DCV in different working positions](image)

Valve employed on the system is a 4/3-way spool (type of the moving body generating the different flow paths) directional control valve (four ports and three possible positions: a, 0, and b, respectively). Figure 2.3 shows three different working regimes:

- regime a when \( x_s > 0 \).
- regime 0 when \( x_s = 0 \).
- regime b when \( x_s < 0 \).

### 2.2.2 Hydraulic circuit decomposition

The circuit is decomposed in two control volumes: control volume A (volume of the fluid between DCV and the piston in the cylinder), denoted as \( CV_a \) and
control volume B (volume of the fluid between piston in the cylinder and DCV) CV\textsubscript{b}. Corresponding pressures \( p_a \) and \( p_b \) and fluid flow rates \( Q_a \) and \( Q_b \) are also denoted (Figure 2.4).

To obtain the hydraulic model, continuity and flow equations are derived for the system at hand.
2.2. Hydraulic modeling

2.2.3 Continuity equation

The basic principle behind the continuity equation is conservation of mass. For the control volumes in the regarded system, the mass flow rate $Q_a$ present in the control volume $CV_a$ is not equivalent to the $Q_b$ present in $CV_b$. This results with the cylinder displacement (crane movement) due to pressure build up in the system (Eq. 2.1).

$$Q_{in} - Q_{out} = V + \frac{V}{\beta} \cdot \dot{p}$$

(2.1)

Since the hydraulic circuit is divided into two control volumes, equation for each is derived separately. Also, while building the equations, cylinder extension (upwards motion) is considered.

$CV_a \rightarrow Q_a - Q_i - Q_{ea} = A_p \cdot \dot{x}_c + \frac{A_p \cdot \dot{x}_c + V_h}{\beta} \cdot \dot{p}_a$

(2.2)

$CV_b \rightarrow -Q_b + Q_i - Q_{eb} = -A_r \cdot \dot{x}_c + \frac{A_r \cdot (x_{c,\text{max}} - \dot{x}_c) + V_h}{\beta} \cdot \dot{p}_b$

(2.3)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Value [Unit]</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$Q_a$</td>
<td>$- [m^3/s]$</td>
<td>Flow rate in the $CV_a$</td>
</tr>
<tr>
<td>$Q_b$</td>
<td>$- [m^3/s]$</td>
<td>Flow rate out of the rod chamber</td>
</tr>
<tr>
<td>$Q_i$</td>
<td>$- [m^3/s]$</td>
<td>Flow rate of the internal leakage (piston to rode chamber)</td>
</tr>
<tr>
<td>$Q_{ea}$</td>
<td>$- [m^3/s]$</td>
<td>Flow rate of the external leakage (out of the $CV_a$)</td>
</tr>
<tr>
<td>$Q_{eb}$</td>
<td>$- [m^3/s]$</td>
<td>Flow rate of the external leakage (out of the $CV_b$)</td>
</tr>
<tr>
<td>$A_p$</td>
<td>$3.117 \cdot 10^{-3} [m^2]$</td>
<td>Cross sectional area of the piston</td>
</tr>
<tr>
<td>$A_r$</td>
<td>$2.41 \cdot 10^{-3} [m^2]$</td>
<td>Cross sectional area of the piston rod</td>
</tr>
<tr>
<td>$\dot{x}_c$</td>
<td>$- [m]$</td>
<td>Piston position in the cylinder</td>
</tr>
<tr>
<td>$x_{c,\text{max}}$</td>
<td>$0.18 [m]$</td>
<td>Maximum piston position in the cylinder</td>
</tr>
<tr>
<td>$p_a$</td>
<td>$- [pa]$</td>
<td>Pressure in the $CV_a$</td>
</tr>
<tr>
<td>$p_b$</td>
<td>$- [pa]$</td>
<td>Pressure in the $CV_b$</td>
</tr>
<tr>
<td>$V_h$</td>
<td>$1.7671 \cdot 10^4 [m^3]$</td>
<td>Volume of the hose</td>
</tr>
<tr>
<td>$\beta$</td>
<td>$7000 \cdot 10^5 [Pa]$</td>
<td>Bulk modulus</td>
</tr>
</tbody>
</table>

Table 2.1: Variables used in continuity equations
2.2. Hydraulic modeling

**Bulk modulus**

When pressurized a hydraulic fluid is compressed causing an increase in density. This is described by means of the compressibility. Reciprocal of the compressibility is stiffness or bulk modulus of the fluid $\beta$. In real systems air will be present in the fluid. The volume percentage at atmospheric pressure will go as high as 20%. As air is much more compressible than the pure fluid, it has, potentially, a strong influence on the effective stiffness of the air containing fluid. The fluid stiffness may be calculated for any temperature and pressure combination regardless of the specific type of mineral oil. For fixed temperature the stiffness is proportional to the pressure rise caused by a compression of the fluid [4].

The ideal bulk modulus (no air in the fluid) is $16000 \cdot 10^5 \text{ Pa}$ (when the reference volumetric ratio of free air in the fluid at atmospheric pressure $\epsilon_0 = 0$). As a rule of thumb, the stiffness under working conditions used for modelling a system should not be set above 10000 bars ($10000 \cdot 10^5 \text{ Pa}$) [4]. Hence, bulk modulus is chosen to be $7000 \cdot 10^5 \text{ Pa}$.

**2.2.4 Flow equation**

The flow restrictions or orifices are a basic means for the control of fluid power. An orifice is a sudden restriction of short length in a flow passage and may have a fixed or variable area (variable for a valve) [4].

Most industrial hydraulic systems involve high-pressure flow through valve openings and the resulting flow is turbulent. A discharge coefficient $C_d = 0.62$ is typically used for the high-pressure valve flow found in industrial hydraulic systems [5].

Substituting turbulent flow coefficient $K_T$ (Eq. 2.3) in general flow equation (Eq. 2.4)

$$K_T = C_d \cdot A_d \cdot \sqrt{\frac{2}{\rho}} \quad (2.4)$$

$$Q = C_d \cdot A_d \cdot \sqrt{\frac{2}{\rho}} \cdot \Delta p \quad (2.5)$$

flow equation is then derived

$$Q = K_T \cdot \sqrt{\Delta p} \quad (2.6)$$
and adjusted for the crane system:

\[
Q_a = \begin{cases} 
K_{v1} \cdot x_s \cdot \sqrt{|p_s - p_a|} \cdot \text{sign}(p_s - p_a) & \text{for } x_s > 0 \\
0 & \text{for } x_s = 0 \\
K_{v2} \cdot x_s \cdot \sqrt{|p_a - p_t|} \cdot \text{sign}(p_a - p_t) & \text{for } x_s < 0 
\end{cases} 
\]  
\tag{2.7}

\[
Q_b = \begin{cases} 
K_{v2} \cdot x_s \cdot \sqrt{|p_t - p_b|} \cdot \text{sign}(p_t - p_b) & \text{for } x_s > 0 \\
0 & \text{for } x_s = 0 \\
K_{v1} \cdot x_s \cdot \sqrt{|p_b - p_s|} \cdot \text{sign}(p_b - p_s) & \text{for } x_s < 0 
\end{cases} 
\]  
\tag{2.8}

Initially, the valve coefficient was assumed \( K_v = 4 \cdot 10^{-7} \), but since upward and downward motion yield in different pressures for the same (absolute) value of the valve opening (i.e. \( x_s = \pm 0.2 \) ), it needs to be tuned further. By the trial and error approach, valve coefficients are chosen:

- \( K_{v1} = 4.16 \cdot 10^{-7} \)
- \( K_{v2} = 3.87 \cdot 10^{-7} \)

Tuning the valve coefficient shows to be leading to the more accurate model.

Internal and external leakage flows are stated as well, even though for the non-faulty system, leakage coefficients are assumed zero and, therefore, leakage flows are also assumed zero:

\[
Q_i = K_{Li} \cdot (p_a - p_b) 
\]  
\tag{2.9}

\[
Q_{ea} = K_{Lea} \cdot p_a 
\]  
\tag{2.10}

\[
Q_{eb} = K_{Leb} \cdot p_b 
\]  
\tag{2.11}

<table>
<thead>
<tr>
<th>Variable</th>
<th>Value [Unit]</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>( x_s )</td>
<td>([-1, 1] ) [%]</td>
<td>Valve spool position</td>
</tr>
<tr>
<td>( K_{v1}, K_{v2} )</td>
<td>(- -)</td>
<td>Valve coefficient</td>
</tr>
<tr>
<td>( K_{Li}, K_{Lea}, K_{Leb} )</td>
<td>(- -)</td>
<td>Leakage coefficient</td>
</tr>
<tr>
<td>( Q_i, Q_{ea}, Q_{eb} )</td>
<td>(- -)</td>
<td>Internal and external leakage</td>
</tr>
<tr>
<td>( C_d )</td>
<td>0.62 [-]</td>
<td>Discharge coefficient</td>
</tr>
<tr>
<td>( A_d )</td>
<td>([- m^2)</td>
<td>Discharge area</td>
</tr>
<tr>
<td>( \rho )</td>
<td>([kg/m^3)</td>
<td>Fluid density</td>
</tr>
</tbody>
</table>

Table 2.2: Variables used in flow equations
2.3 Mechanical modeling

2.3.1 Force equation: Newton’s second law

Newton’s Second Law states that the sum of all forces $\sum F$ acting on the object is equal to its mass $m$ multiplied by the acceleration of the object $a$. Adjusted for the cylinder in question, the equation is given:

$$\sum F_{cylinder} = M_{eq} \cdot \ddot{x}_c$$  \hspace{1cm} (2.12)

Sum of the forces acting in the cylinder are represented on the free body diagram shown in Figure xx.

$$\sum F_{cylinder} = F_a - F_b - F_f - F_g$$  \hspace{1cm} (2.13)

Force $F_a$ is acting on the piston upwards from the piston chamber in the cylinder and $F_b$ downwards from the rod chamber side. $F_f$ represents friction force and $F_g$ is a gravitational force of the cylinder.

![Free Body Diagram](image)

**Figure 2.5:** Forces acting on the cylinder

2.3.2 Friction force

Friction is a force phenomenon which opposes relative movement between two surfaces in contact [6]. Friction force vector is reverse-proportional to the piston movement direction: while cylinder is retracting, $F_f$ acts upwards, and while extending, $F_f$ acts downwards. Friction force, furthermore, is a combination of three components:
2.3. Mechanical modeling

- Coulomb friction $F_c$. The Coulomb friction is a constant friction contribution and thereby the (absolute) value is not dependent on the velocity (graph a, Figure 2.6) [6].

- Viscous friction $F_v$. Assumed to be proportional to the velocity and expressed as a function of a viscous friction coefficient $B$ multiplied with the velocity (graph b) [6].

$$F_v = B \cdot \dot{x}_c$$  \hspace{1cm} (2.14)

- The Stribeck friction $F_{stb}$. Phenomenon influencing the operation at low velocities is the Stribeck effect (graph c). The Stribeck effect is a friction contribution at low velocities, which is decreasing exponentially from the difference between the stiction (Breakaway friction force) and the Coulomb force [6].

$$F_{stb} = (F_{brk} - F_c) |\dot{x}_c|$$  \hspace{1cm} (2.15)

Based on the LuGre model, the steady-state friction force for constant velocity (graph d) can be stated as [7]:

$$F_f = (F_c + F_{stb}) \cdot \text{sign}(\dot{x}_c) + F_v$$  \hspace{1cm} (2.16)
2.3. Mechanical modeling

2.3.3 System equation

Mathematical model can now be derived:

\[ M_{eq} \ddot{x}_c = p_a \cdot A_p - p_b \cdot A_r - ((F_c + F_{stb}) \cdot \text{sign}(\dot{x}_c) + F_0) - m_{crane} \cdot g \] \hspace{1cm} (2.17)

where the equivalent mass \( M_{eq} \) is a crane mass translated and acting on the top of the cylinder.

2.3.4 Equivalent Mass

To calculate the equivalent mass, Law of conservation of energy is employed. Since kinetic energy at the top of the cylinder is equal to one at the center of the mass of the crane, the equation can be stated as:

\[ E_{k1} = E_{k2} \Rightarrow \frac{M_{eq} \cdot \dot{x}_c^2}{2} = \frac{m_{crane} \cdot \dot{x}_{crane}^2}{2} \] \hspace{1cm} (2.18)

where \( \dot{x}_c \) represents the change of the piston position and \( \dot{x}_{crane} \) represents the change of the crane (center of the mass) position. Mass of the crane is assumed to be \( m_{crane} = 224 \text{kg} \)

Further, assuming the almost-vertical movement of the center of the mass, equivalent mass is considered constant:

\[ M_{eq} = \frac{m_{crane} \cdot \dot{x}_{crane}^2}{\dot{x}_c^2} \] \hspace{1cm} (2.19)

By using basic trigonometry (denoted in the figure bellow), the relationship between piston position and crane position is obtained as:

\[ \cos(\theta) = \frac{x_c}{L_1} = \frac{x_{crane}}{L_2} \Rightarrow x_{crane} = \frac{x_c \cdot L_2}{L_1} \] \hspace{1cm} (2.20)
Implementing Eq. 2.17 into Eq. 2.16 yields to the equivalent mass acting on the top of the cylinder:

\[ M_{eq} = m_{crane} \cdot \left( \frac{L_2}{L_1} \right)^2 = 7671.23\text{kg} \]  
(2.21)
Chapter 3

Open-loop Model Validation

3.1 Experimental setup

All the experiments done on the crane setup, both for model validation and later for the fault detection, are of the same nature. Multiple step-input is used since it will cover wide range of the system process dynamics, including transients and friction force effect.

Crane is given an input in terms of valve opening. Data is obtained using Simulink Real Time and Simulink crane model given. Sample time used was $T_s = 1ms$.

This is possible due to system being equipped with pressure sensors, position sensor for piston position, flow meter and leakage flow meters. Opening of the valve is controlled and monitored directly. Variables measured from all the experiments are given in the table bellow:

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Number of sensors</th>
<th>Variables measured</th>
</tr>
</thead>
<tbody>
<tr>
<td>DCV sensor</td>
<td>1</td>
<td>$x_s$</td>
</tr>
<tr>
<td>Position sensor</td>
<td>1</td>
<td>$x_c$</td>
</tr>
<tr>
<td>Pressure sensor</td>
<td>4</td>
<td>$p_s, p_t, p_f, p_h$</td>
</tr>
<tr>
<td>Flow meter</td>
<td>1</td>
<td>$Q_s$</td>
</tr>
<tr>
<td>Leakage flow meter</td>
<td>2</td>
<td>$Q_t, Q_{in}, Q_{eb}$</td>
</tr>
<tr>
<td>Temperature sensor</td>
<td>1</td>
<td>$T_s$</td>
</tr>
</tbody>
</table>

Table 3.1: Sensors in hydraulic circuit

3.2 Validation

To validate the mathematical non-linear model, hydraulic and mechanical models are combined in a simulink model, representing the system.
3.2. Validation

3.2.1 Simulink model

Data obtained by the experiments include measured source (pump) pressure denoted as $p_s$ and tank pressure denoted as $p_t$. This two variables will be two inputs to the simulink model and third input is a valve opening position.

After processing the data, open-loop model ends with five outputs: three are the remaining variables measured by sensors, i.e. piston position $x_c$, piston side pressure $p_a$ and rod side pressure $p_b$; other two are calculated and taken from the simulation: change in piston position - piston velocity $\dot{x}_c$ and change in piston velocity - piston acceleration $\ddot{x}_c$.

![Figure 3.1: Simulink model of the hydraulic crane setup](image)

3.2.2 System noise

For better accuracy (and also for future purposes) process $v$ and measurement noise $n$ are taken into account and added to the model as stated:

$$\dot{x}(t) = f(x(t), u(t)) + v(t)$$

$$y(t) = g(x(t), u(t)) + n(t)$$

Both are considered white Gaussian noise with zero mean and a respective variance.

It is possible to capture measurement noise directly from the measurement. By obtaining the data when the crane is in a steady-state, and removing the mean value from the data-set, variance can be determined for each variable. As such, it is implemented in the model:
3.3 Results

- measurement noise variance for position: $\sigma_{\text{position}}^2 = 1.7 \cdot 10^{-6}$
- measurement noise variance for pressure: $\sigma_{\text{pressure}}^2 = 1.4 \cdot 10^9$

On the other hand, it is difficult to determine the process noise as it is not possible to directly observe the process needed to be estimated, but also due to uncertainties in the system [8]. Process noise is therefore chosen as:

- process noise variance for position: $\sigma_{\text{position}}^2 = 1 \cdot 10^{-3}$
- process noise variance for pressure: $\sigma_{\text{pressure}}^2 = 1 \cdot 10^5$

Due to system being non-linear it needs to be verified whether the system dynamics and transient behaviours are modeled correctly and what is the degree of accuracy.

Each data-set obtained by the experiments is compared with the data-set from the simulation. Piston side pressure, rod side pressure and piston position are the variables that will be compared.

3.3 Results

![Graphs showing comparison of measured and calculated values for piston side pressure, rod side pressure, piston position, and valve opening.](image)

*Figure 3.2: Multiple step input ±10% and ±30%*
Figure 3.3: Multiple step input ±30% and ±60%

Figure 3.2 and 3.3 show comparison of two data-sets with their respective simulated data. In both cases simulated piston position is accurate to a high degree. Piston side pressure comparison shows that the main dynamic behaviours are modeled properly. On the other hand, inconsistencies in rod side pressure are mainly influenced by valve coefficients as they were used as a tuning parameter. Any other set of valve coefficients would lead to a greater offset in both pressures.

Wide range of valve opening is covered and both simulated data-sets have similar accuracy level. This indicates that the model accuracy does not depend on the input in terms of the valve opening.

Overall inconsistencies could be also caused by a number of factors such as parameter approximation, input signal noise or offset in the sensors. Regardless, derived mathematical model is considered accurate.
Chapter 4

Fault Detection and Diagnosis

In the following chapter, the working principle of Fault Detection and Diagnosis (FDD) is briefly introduced. Analysis of the experimental application of Extended Kalman Filter (EKF) for the hydraulic crane model is done and the obtained results are discussed.

4.1 Introduction to FDD

First, the difference between fault detection and fault diagnosis (isolation) needs to be established. Fault detection system tells if a fault occurred. Fault diagnosis goes further into analysis and determines the location in the system where the fault occurred and estimates the severity of the fault.

Fault detection and diagnosis tackles the following problem: for a system to be reliable and safe, automated supervision needs to be ensured through monitoring and automated protection. In the case when exceeding a threshold leads to system operating in a safety-critical state, the system should automatically enter a fail-safe state, which is often an emergency shut down [2]. FDD methods are distinguished as: data-based and model-based methods [2]. A figure below shows the principle of a model-based FDD in a block diagram.
Using available input and output information from the observed system, FDD generates a fault indicating signal, i.e., residual. Based on the residual, system is said to be non-faulty (residual will be zero or close to zero), or faulty (for non-zero residual) [9].

### 4.2 Extended Kalman Filter

Extended Kalman Filter, a non-linear interpretation of Kalman filter, is a model-based FDD method based on linearization about the current state estimation [8].

In order to detect leakage faults, EKF is applied to the hydraulic crane model. Leakage coefficients are parameters considered in the system modeling. Their parameter estimates are expected to detect faults. This is done by augmenting the system.

#### 4.2.1 State of the art

In their paper [10], Liniger, Pedersen, and Soltani present a brief review of state of the art for designing reliable fluid power pitch systems. Review of methods is limited to the work publicly available whereby industry research is not included unless evident from patents [10].
Choux, Tyapin and Hovland in [11] use two approaches to determine internal and external leakage flows in an experimental hydraulic test bed representing a wind turbine: residual errors based on different assumptions on the leakage using Extended Kalman Filter (EKF) and leakage detection from augmented states using State Augmented Extended Kalman Filter (SAEKF).

Both approaches are based on source pressures and cylinder piston position measurements as inputs. The non-linear model was verified through the experimental data for state estimation.

Results presented show that both EKF and SAEKF can detect both external and internal leakages in the hydraulic system. The computational time using SAEKF method was said to be approximately 12 times higher than those required by EKF [11], thus it is suggested to use a combination of EKF for leakage detection and SAEKF for the leakage isolation and diagnosis.

Since in [11] leakage flows as augmented states are used, for the purpose of this research, similar approach is taken. SAEKF will be used with internal and both external leakage coefficients as augmented states.

4.2.2 EKF equations

For the non-linear discrete system given by:

$$x_{k+1} = f(x_k, u_k) + v_k \quad (4.1)$$

$$y_k = g(x_k, u_k) + n_k \quad (4.2)$$

process noise $v_k$ and measurement noise $n_k$ are stochastic variables assumed to be statistically independent with a Gaussian distribution with zero mean and the covariance matrices $M$ and $N$, respectively.

EKF state estimation is done through the iteration process, for each time-step $k$, using following algorithm of prediction and update equations as stated in [2]:

**Update**

Predicted next state estimate:

$$\hat{x}_{k+1|k} = f(\hat{x}_k, u_k) \quad (4.3)$$

Predicted state error covariance:

$$P_{k+1}^- = AP_kA^T + M \quad (4.4)$$
4.2. Extended Kalman Filter

Correction

Kalman gain:

\[ K_{k+1} = P_{k+1}^{-} C_T [C P_{k+1}^{-} C + N]^{-1} \]  \hspace{1cm} (4.5)

Next state estimate:

\[ \hat{x}_{k+1|k+1} = \hat{x}_{k+1|k} + K_{k+1} [y_{k+1} - C \hat{x}_{k+1|k}] \]  \hspace{1cm} (4.6)

State estimate error covariance:

\[ P_{k+1} = [I - K_{k+1} C] P_{k+1}^{-} \]  \hspace{1cm} (4.7)

The derivation of the Kalman filter is valid only for the linear systems, therefore Jacobian system process matrices \( A \) and \( C \) are needed to be linearized around the predicted state estimate for each time-step \( k \) [8]:

\[ A_{k+1|k} = \left. \frac{\partial f(x_k, u_k)}{\partial x_k} \right|_{\hat{x}_{k+1|k}, u_k} \]  \hspace{1cm} (4.8)

\[ C_{k+1|k} = \left. \frac{\partial g(x_k, u_k)}{\partial x_k} \right|_{\hat{x}_{k+1|k}, u_k} \]  \hspace{1cm} (4.9)

4.2.3 State-space model

State-space model for the system at hand is obtained:

State, input and output (measurement) vectors

\[
\begin{bmatrix}
  x_1 \\
  x_2 \\
  x_3 \\
  x_4 \\
  x_5 \\
  x_6 \\
  x_7
\end{bmatrix} =
\begin{bmatrix}
  x_c \\
  \dot{x}_c \\
  p_a \\
  p_b \\
  K_{Li} \\
  K_{Lea} \\
  K_{Leb}
\end{bmatrix}
; \\
\begin{bmatrix}
  u_1 \\
  u_2 \\
  u_3
\end{bmatrix} =
\begin{bmatrix}
  u_1 \\
  u_2 \\
  \dot{u}_3
\end{bmatrix}
; \\
\begin{bmatrix}
  y_1 \\
  y_2 \\
  y_3
\end{bmatrix} =
\begin{bmatrix}
  y_1 \\
  y_2 \\
  y_3
\end{bmatrix}
\]

(4.10)
4.2. Extended Kalman Filter

Differential state equations

\[ \dot{x} = \begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \\ \dot{x}_3 \\ \dot{x}_4 \\ \dot{x}_5 \\ \dot{x}_6 \\ \dot{x}_7 \end{bmatrix} = \begin{bmatrix} \dot{x}_c \\ \dot{\hat{p}}_a \\ \dot{\hat{p}}_b \\ K_{Li} \\ K_{Lea} \\ K_{Leb} \end{bmatrix} \]

for \( x_s > 0 \):

\[
\begin{bmatrix}
  x_2 \\
  \frac{A_p \cdot x_1 + V_h}{(K_{c1} \cdot u_1 \cdot \sqrt{|u_2 - x_3|} \cdot \text{sign}(u_2 - x_3)) - x_5 \cdot (x_3 - x_4) - x_6 \cdot x_3 - A_p \cdot x_2} \cdot \beta \\
  \frac{(K_{c2} \cdot u_1 \cdot \sqrt{|u_3 - x_4|} \cdot \text{sign}(u_3 - x_4)) + x_5 \cdot (x_3 - x_4) - x_7 \cdot x_4 + A_r \cdot x_2} \cdot \beta \\
  A_p \cdot x_1 + V_h \\
  A_r \cdot x_{c_{max}} - x_1 + V_h \\
  0 \\
  0 \\
  0 \\
\end{bmatrix} = (4.11)
\]

for \( x_s < 0 \):

\[
\begin{bmatrix}
  x_2 \\
  \frac{A_p \cdot x_1 + V_h}{(K_{c1} \cdot u_1 \cdot \sqrt{|u_3 - u_3|} \cdot \text{sign}(u_3 - u_3)) - x_5 \cdot (x_3 - x_4) - x_6 \cdot x_3 - A_p \cdot x_2} \cdot \beta \\
  \frac{(K_{c2} \cdot u_1 \cdot \sqrt{|u_4 - u_2|} \cdot \text{sign}(u_4 - u_2)) + x_5 \cdot (x_3 - x_4) - x_7 \cdot x_4 + A_r \cdot x_2} \cdot \beta \\
  A_p \cdot x_1 + V_h \\
  A_r \cdot x_{c_{max}} - x_1 + V_h \\
  0 \\
  0 \\
  0 \\
\end{bmatrix} = (4.12)
\]

Covariance matrices and initial conditions

Assuming noises are stationary, covariance matrices are considered constant. Thus, \( N \) and \( M \) are diagonal matrices chosen as:

\[ N = \text{diag}[1.7e-6, 1.4e9, 1.4e9] \]

(4.13)
\[ M = diag[1e-3 \ 1e-5 \ 1e5 \ 1e5 \ 1e-16 \ 1e-11 \ 1e-13] \] (4.14)

It should be noted that covariance matrix \( N \) values correspond to respective measurement noise variance as stated in the section 3.2.2. Covariance matrix \( M \) is used as a tuning parameter for the EKF.

Initial state estimate \( \hat{x}_0 \) needs to be chosen which is usually first measurement value when the data is available or otherwise, reasonably assumed values. Finally, the initial state error covariance is chosen to be:

\[ P_o = M \cdot 10 \] (4.15)

### 4.3 EKF results

Once the simulink model (Figure 4.2) including the system process and the EKF is built, its implementation needs to be validated.

![EKF Simulink model](image)

**Figure 4.2: EKF Simulink model**

First, the data-set used for validating the hydraulic system model is used (shown in the Figure 3.3). Input to the EKF are vectors \( u \) and \( y \) from Eq. 4.10, experiment obtained measurements. No leakage is introduced to the simulation.
4.3. EKF results

As seen in the Figure 4.3, EKF is able to estimate output accurately. Estimated pressures are more noisy than measurements as expected, while piston position estimate is almost identical as the measured.
While from the Figure 4.3 it could easily be concluded that the EKF is correctly implemented, that claim would be incomplete without first observing the next figure. Since the scope of this research is to investigate State Augmented EKF implementation, Figure 4.4 gives information on how augmented states are well estimated.

Estimated leakage coefficients fail to follow reference signal, or at least, deviation from the expected values is significant. On the other hand, both estimated external leakage coefficients gravitate around zero, while internal leakage coefficient estimate discrepancy increases with time.

This could be explained by the fact that the leakage coefficients estimation contain some information from interacting with pressure state estimates. Moreover, fluctuating input (valve opening) also needs to be taken into consideration. Further analysis will be carried out using the data-set obtained with a simple constant for a valve opening as an input. Again, leakage is not introduced.

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Figure 4.5: Estimated and measured output comparison
4.3. EKF results

Results obtained using constant as an input again show good output estimation and poor leakage coefficient estimation, although with more stable values. Next, the same data-set will be used but with introducing the external leakage $K_{Lea} = 3e^{-11}$ after one second into simulation.

**Figure 4.6:** Estimated leakage coefficients

**Figure 4.7:** Estimated and measured output comparison
4.3. EKF results

When the leakage is introduced to the process, output estimation remains fairly accurate, but more noisy. Introduced leakage leads to both piston and ring side pressure drop as expected. Leakage coefficient estimation shows more information now: although values still deviate beyond desired, abrupt change can be seen at $t = 1\text{s}$ for external leakage coefficient $K_{Lea}$ which indicate good EKF implementation. Drawback is that the change in $K_{Lea}$ results also with the change in estimation of $K_{Leb}$.

Conclusion is that the State Augmented EKF could still be a good choice of method for estimating leakage coefficients, but the approach should be modified. Instead of having three augmented states at once, system should be augmented with one leakage coefficient at the time, leading to having five state augmented system three times in order to being able to capture all planned leakages.

Figure 4.8: Estimated leakage coefficients
Chapter 5

Conclusion

5.1 Discussion

In the introduction, the goal of the project was said to be application of the EKF on the experimental setup in order to estimate the artificially implemented leakage. Internal and external leakage was only considered; internal representing leakage due to piston seal being damaged/worn out and external representing fluid loss from piston side or rod side control volumes.

While obtaining the model, non-faulty system was considered. Mathematical model derived consists of mechanical and hydraulic parts which were modeled separately and later combined in a simulink model. Due to complexity of the system, various assumptions and approximations were made.

Hydraulic crane was employed as an experimental setup in order to obtain measurements which will then be used as input to the simulation and as a reference for validation. System model was validated and said to be sufficiently accurate for EKF implementation.

FDD is performed in such way that the EKF, a non-linear version of regular Kalman filter, was adapted for the hydraulic system and augmented with leakage coefficients as states. Their estimation was expected to detect faults. Although EKF was correctly implemented, augmenting the state-space model with three states did not yield to successful results. SAEKF failed to estimate leakage coefficients even for the non-faulty system. It is concluded that the SAEKF should be performed by augmenting only one leakage coefficient at the same time.

5.2 Future work

In addition to work presented, various improvements would lead to better performance of both obtained mathematical model and the EKF leakage estimation.
5.2. Future work

**Better model accuracy**

- Equivalent mass was assumed constant while in practice it is a function of the piston position.
- Since calculated pressures show inconsistencies compared to the measured pressures, analysing unaccounted valve leakages could mitigate the discrepancy.
- Further analysis of parameters used for modeling the friction force would lead to better tracking system dynamics.
- Deeper analysis of Bulk modulus should be carried out.

**EKF estimation**

- Reducing the state-space model to a five state EKF with one leakage coefficient as augmented state should solve the problem of current augmented states not being able to estimate true leakage coefficient.
- Implementing bank of such EKFs in order to estimate all considered leakage coefficients.
Bibliography


