Modeling, Identification and Control Design for an Electro-Hydraulic Rotator

Examensarbete utfört i Reglerteknik vid Tekniska högskolan i Linköping
av
Andrej Zanhar

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Handledare: Prof. Anton Shiriaev
Umeå Universitet
PhD. Pedro Xavier Miranda LaHera
Umeå Universitet

Examinator: Prof. Svante Gunnarsson
ISY, Linköpings universitet

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Robotic manipulators have been introduced in industry as a form of increasing productivity. Today, there exist an interest to enlarge the application of these manipulators to outdoor environments. Forestry cranes used in the forestry industry are a clear example. A long term goal in this industry is the development of autonomous systems to increase the logging efficiency. In this thesis, we consider how to control the rotator of these cranes, which is an electro-hydraulically actuated motor, and is used to control the end effector tool.

Control system design for the rotator is a challenging task since the sensing is not available to full extent. The main reason is the harsh environment that these machines are exposed to and sensors such as encoders are very fragile and can not be used. In this thesis we use alternative sensing devices, such as a magnetic sensor and a stereo camera. In the case of the camera we face a problem with big delay. A prediction method has been used to compute desired values.

Due to various reasons certain measuring devices can not be used in the industry. We consider four cases for control system design where different combinations of available sensors have been used. Initially angular position of the rotator is controlled using only the magnetic sensor. A cascade control setup is used where pressure and position are measurable, first using the magnetic sensor and later using the camera. When only pressure measurements are available identified models have replaced sensors for position feedback.

All tests and experiments have been done using a scaled version of a real forestry crane. The available crane has similar configuration and dynamics as the real one and is therefore useful for experimental purposes.
Abstract

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All tests and experiments have been done using a scaled version of a real forestry crane. The available crane has similar configuration and dynamics as the real one and is therefore useful for experimental purposes.
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Chapter 1

Introduction

1.1 Problem Formulation

To remain in the top, manufacturers of forestry machines have turned their eyes on automatic control. It is a new approach for the industry and few implementations have yet been done. It is a long term goal for the forestry industry to develop autonomous forestry machines while semi-autonomous is a short time goal.

There are mainly two types of off-road vehicles used in the forestry industry: the harvester which fells and delimbs the trees, and cuts the trunk into logs of a predetermined size, and the forwarder (see Fig. 1.2), which collects the logs in a tray and carries them to different locations. These two types of vehicles have similar on-board hydraulic manipulators (cranes). In today’s technology, the crane is manually controlled by a human operator from a chair. It takes years for a driver to feel fully comfortable controlling the crane. The automation of the crane is therefore important and it could remove some of the responsibilities from the driver and thereby simplify the situation and shorten the learning period. The crane consists of several parts (links). To fully control the crane each link has to be controlled not only individually but also with consideration to other links. Each type of crane uses a different end-effector tool. In this thesis, the rotator from a forwarder is analyzed.

The rotator is affected by big external forces when used in extreme and harsh environments. It easily bumps into trees and other obstacles. Log handling requires large forces and drivers are normally not gentle since everything is aimed to be time effective. These reasons, among others, contribute to the fact that an external sensing device mounted on the gripper would not survive for long. Position sensors such as encoders are very fragile. However pressures and flows are easier to measure. These sensors are placed inside the hydraulic system and are not as affected by the external disturbances.

In order to design high performance control systems, accurate models of system dynamics are required. The task of modeling an electro-hydraulic crane is far from simple, due to the highly nonlinear nature of its dynamics. For example, parameters such as bulk modulus change drastically with oil temperature.
The mechanical construction is also nonlinear since parameters such as external payload and inertias vary and are usually unknown. Uncertainties, such as external disturbances, leakage and friction are unknown and can not be modeled or compensated accurately. They also have a tendency to change with structural condition and age [3]. Models can describe the system dynamics to some extent but certain phenomena have to be dealt with in other ways. This contributes to the complexity of controlling such hydraulic manipulators.

A block diagram of the entire crane can be seen in Fig. 1.1. The system consists of an electro-hydraulic subsystem and a mechanical subsystem respectively. The desired motion is determined by a human-machine interface and generated by a control system. A number of measurement devices are used to measure positions, pressures, currents and other variables.

**Figure 1.1.** A block diagram of the crane. The HMI determines desired trajectories which are controlled by a control system. The controller feeds the electro-hydraulic system with a current that further provides pressure. The torque produced by the hydraulics is fed into the mechanical system that generates a motion. The motion is measured by sensing devices and used for monitoring(HMI) and control.
1.1. PROBLEM FORMULATION

The main subject for this thesis is to model the dynamics of the rotator and to identify the models, such that model-based control can be applied. For position feedback, identified models, a magnetic sensor for position, and a camera are used to estimate the true position. Even though our system allows us to measure pressure, this work also considers scenarios where that might not be possible. The main questions that this thesis aims to answer are the following:

- **Case I**: How can the rotator be controlled when the angular position is the only measurable variable?
- **Case II**: Which control designs can be used when both pressure and position are measurable?
- **Case III**: Is it possible to control the position using just pressure sensors?
- **Case IV**: How well can position be controlled using pressure sensors and a stereo camera?

These cases will be referred to as I, II, III and IV respectively throughout this entire work.
1.2 Experimental setup

All experiments and tests are carried out at the Smart Crane Lab located at the Department of Applied Physics and Electronics, Umeå Universitet. The laboratory is equipped with an electro-hydraulic crane CRANAB model 370RCR (see Fig. 1.3). The crane is a scaled version of a real forwarder crane with similar configuration and dynamics.

![Image of the Smart Crane Lab](image)

**Figure 1.3.** The Smart Crane Lab, Umeå Universitet. Next to the crane the PC and the dSPACE are seen along with a chair, the same as used in real cabs.

1.2.1 Hardware overview

The hydraulic hardware in the Smart Crane Lab consists of [13]

- hydraulic motor for the rotator manufactured by Valmet,
- hydraulic cylinders for the rest of the links manufactured by Valmet,
- a unit containing six servo-valves from Sauer-Danfoss model L90LS,
- the power supply for this system consists of an electrical motor, controlling a hydraulic pump (type H4-010214-132) set to provide a constant supply pressure of 180 bars for the whole system operation.

The associated measurement equipment in the laboratory includes:
• encoders of 4000 pulses/turn, used to measure the angular position of various links. Note that the angular position of the rotator is not measured by these sensors.

• pressure transducers (HD 3403-10-C3.39) capable of sensing in a range of \([0,200]\) bar.

The crane can be directly manipulated from a chair (see Fig. 1.4.a), which is of the same type as the ones mounted in the cabins of real forwarders. This chair contains buttons and joysticks (see Fig. 1.4.b) that allow the driver to have full control over the whole machine operation including the crane.

![Figure 1.4.](image)

(a) A chair from a real forwarder. The chair is connected to the crane so that it can be manually operated. (b) The two arms with joysticks and buttons. These are used to perform operations on the crane.

For the control of the crane as well as the implementation of algorithms a dSPACE Prototyping Hardware [1] is used. The processing unit applied in this particular case is the MicroAutoBox (MABX), which directly controls the available I/O features, such as the Electronic Control Unit, the AD and DA converter units, the digital I/O and CAN subsystems [13].

In order to provide a sufficient range of current to drive the servo valves a RapidPro [15] unit is installed. The RapidPro contains a Power Unit (PU), which transforms the low voltages generated by the MABX to appropriate currents for the valve solenoids. The current in each circuit can be measured. Furthermore, there is a so-called Signal Conditioning Unit (SCU) which can handle the incoming measurement signals to voltage levels needed to be fed to the MABX [13]. Finally, a Dell PC is used to monitor and serve as an on-line user interface through the use of Control Desk. The interface uses compiled data from Simulink in a way that allows the user to monitor all possible variables, scopes and sources that exist in a Simulink file. Fig. 1.5 shows an example of Control Desk that has been used in this thesis. This example includes blocks for choosing and altering the reference signal and gain, controller and graphical presentation of the signals to mention a few.
Figure 1.5. The Control Desktop interface. The interface is used to monitor different signals (pressure, position, current and more). It is also used to change variables such as gains in a PID controller in real time. The choice of reference trajectory is also done using the interface.

1.2.2 Magnetic sensor

The magnetic sensor was mounted onto the rotator due to the lack of sensors for position. The addition of such a sensor is today not feasible due to reasons mentioned before. The sensor consists of a metallic disk attached to the rotator
1.2. EXPERIMENTAL SETUP

according to Fig. 1.6.b. A total of thirty-six magnets are evenly spread out along
the edge of the disk resulting in a resolution of ten degrees (see Fig. 1.6.a). A
magnetic sensor senses the magnets and the data is treated to obtain position
values.

![Figure 1.6](image)

(a) CAD model of the disk designed for the rotator’s angular position
sensing. Thirty six evenly spread out magnets can be seen along the edge of the disc.
These magnets are recognized by a sensor to determine the position; (b) Frontal view
of the installation of the disk. It is mounted just above the gripper at the wrist of the

1.2.3 Bumblebee Camera

The camera used in this thesis is of type, Bumblebee2. The camera is a stereo
camera and has the ability to capture two types of images [16], a color image
($RGB$) and a depth image ($XYZ$) as displayed in Fig. 1.7. A pixel $XYZ(i,j)$
in the depth image contains the 3D point $(x_{ij}, y_{ij}, z_{ij})$ that correspond to the pixel
$RGB(i,j)$ in the color image [16]. The user interface and algorithms used to

![Figure 1.7](image)

(a) The Bumblebee2 camera has the ability to capture 2 different types of
images. In (a) a depth image of the rotator and the log can be seen. In (b) a color image
of the same.

compute rotator position, log position and angle will be described shortly. The
first step is to find the rotator and that is done by letting the user define the center position (in the color image) of the rotator in the user interface. Based on this the algorithm constructs an area, $A$, around the corresponding pixel in the depth image [16]. The position is then decided by the median of the 3D points in $A$,

$$
x_g = \text{median}(x_{ij}), \quad y_g = \text{median}(y_{ij}), \quad z_g = \text{median}(z_{ij})
$$

To find the log the 3D points of the log are separated from other points by first excluding points that are far away from the rotator. Second, points with a color that does not coincide with the log are excluded. A method based on saturation is used to separate the points of the log from the points of the rotator and the gripper. Finally the angle of the log is calculated as follows. Assuming that $P$ is a set of all 3D points in a color thresholded XYZ image, the median of the gradient is calculated by [16]

$$
g = \text{median} \frac{dz}{dx} = \text{median} \frac{z_p - z_g}{x_p - x_g},
$$

where $x_p, y_p, z_p$ are the coordinates of each point in $P$ seen from $(x_g, y_g, z_g)$. The angle of the log can be calculated as

$$
\omega = \tan^{-1}(g)
$$
Chapter 2

Modeling

The electro-hydraulic nature of this system requires specific models in terms of hydraulics, electronics and mechanics.

2.1 Modeling of the mechanical dynamics

The rotating motion of a mechanical system can be described by Newton’s second law [7]

\[ J \cdot \ddot{\theta} = \tau, \]  

(2.1)

where \( J \) is the inertia of the mechanical link, \( \theta \) is the angular position and \( \tau \) is the total external torque. The torque \( \tau \) can be expressed as

\[ \tau = \tau_{\text{hyd}} - \tau_{\text{friction}} - \tau_{\text{disturbance}}, \]  

(2.2)

where \( \tau_{\text{hyd}} \) is the torque provided by the hydraulic system, \( \tau_{\text{friction}} \) is friction affecting the system and \( \tau_{\text{disturbance}} \) is external disturbance. If (2.2) is substituted into (2.1) the following equation is obtained

\[ J \cdot \ddot{\theta} = \tau_{\text{hyd}} - \tau_{\text{friction}} - \tau_{\text{disturbance}} \]  

(2.3)

2.1.1 Friction

Friction is a force that acts in the opposite direction of motion. The most commonly used description of the friction phenomenon is [6]

\[ F = F_C \cdot \text{sgn} \, v, \]  

(2.4)

where the friction force \( F_C \) is proportional to the normal load, i.e \( F_C = \mu \cdot F_N \), and \( v \) is the velocity. It is clear that the friction is described as an ideal relay, see Fig. 2.1 (a), and is referred to as the Coulomb friction. The above mentioned model does not define the friction force for zero velocity and the force can take
any value between $F_C$ and $-F_C$. Note that the two limits, positive and negative can have different value. Thus Coulomb friction is defined by the map

$$F = \begin{cases} F_{Cp} & \text{if } v > 0, \\ -F_{Cn} & \text{if } v < 0. \end{cases} \quad (2.5)$$

where $p$ and $n$ represent the positive and negative direction respectively. Such systems are the result of imperfections in manufacturing, i.e they are not symmetrical.

Expressions for the friction force caused by the viscosity of lubricants were introduced in the mid 19th-century by Osbourne Reynolds. The term *viscous friction* is used to describe this phenomenon [6]

$$F = F_v \cdot v \quad (2.6)$$

The viscous friction is combined with the Coulomb friction, see Fig. 2.1.b. The combination of the two gives us an expression for $\tau_{friction}$

$$\tau_{friction} = b \cdot \dot{\theta} + \tau_{Coulomb} \cdot \text{sgn} \dot{\theta}, \quad (2.7)$$

where $b$ represents the viscous friction coefficient and $\tau_{Coulomb}$ the contribution of the Coulomb force i.e $F_{Cp}$ or $F_{Cn}$. If (2.7) is substituted into (2.3) we obtain

$$J \cdot \ddot{\theta} = \tau_{hyd} - b \cdot \dot{\theta} - \tau_{Coulomb} \cdot \text{sgn} \dot{\theta} - \tau_{disturbance}, \quad (2.8)$$

which describes the dynamics of the mechanical part.
2.2 Modeling of the Hydraulics

The rotator is controlled by a four-way valve. In Fig. 2.2 the schematic picture of such a system is shown. The Load is in our case represented by the gripper with moment of inertia $J$, the torsional spring rate $k_t$ and the viscous friction coefficient $b$. The rotary actuator is connected to the rotating mass and can also be observed in Fig. 2.3. The in and outflow of hydraulic fluid to the actuator is controlled by the four-way control valve, shown to the left of the actuator. The displacement of the spool valve is denoted $x$, where positive direction is according to Fig. 2.2. When the valve moves in positive $x$-direction, the flow $Q_A$ is directed into side A, whereas $Q_B$ is directed out from side B. A pump is used as a hydraulic power source, it pumps hydraulic fluid from the reservoir into the spool valve which, as explained above, controls the path of the fluid into the actuator. The pressure in the supply line of the hydraulic fluid is controlled by a high-pressure relief valve.

![Figure 2.2](image.png)

**Figure 2.2.** Schematic of a four-way valve-controlled rotary actuator. A pump supplies a pressure and a flow into the system. The hydraulic fluid flows into either port A or port B depending on the position of the spool. The direction of the fluid determines movement of the actuator.
Figure 2.3. Hydraulic rotary actuator [4]. Hydraulic fluid can flow into and out from the actuator in both openings. The flow is determined by the position of a spool valve. Depending on flow direction the actuator rotates either clockwise or counter clockwise.

Since the modeling of the load has been made in the previous section no such analysis will be made here.

In the case when internal disturbances, nonlinearities caused by friction, and the efficiency of the components is neglected, the torque produced by the hydraulic system is described as [11],

$$ T = D_a (P_A - P_B), \quad (2.9) $$

where $D_a$ is the volumetric displacement $V_a$ (actuator) lumped together with $\eta_a$, being the efficiency of the actuator. $P_A$ and $P_B$ are the pressures within the actuator.

Pressure and flow can be described as [10]

$$ dP = \frac{\beta}{V} dV $$

$$ dV = \sum Q \quad (2.10) $$

where $\beta$ is the bulk modulus. Thus the dynamics of pressure in the actuator can be described by the sum of flows [12]

$$ \dot{P}_A = \frac{\beta}{V_A} (-C_l P_A - D_a \dot{\theta} + Q_A) \quad (2.11) $$

$$ \dot{P}_B = \frac{\beta}{V_B} (-C_l P_B - D_a \dot{\theta} + Q_B), $$
where $V_A$ and $V_B$ are the volumes of the two chambers. The internal leakage coefficient, $C_l$, corresponds to the flow from one chamber to the other, thus being negative. $\theta$ is the rotor displacement (see Fig. 2.3) and $D_a \dot{\theta}$ is the flow that is generated by the moving plate in the actuator. The input and output flows to and from the rotor chambers are denoted $Q_A$ and $Q_B$ respectively, and the expressions for these flows are presented later in (2.18).

The pressure transients that result from fluid being compressible are neglected. If the distance between the valve and the actuator is small and if there exists a small amount of fluid throughout the transition lines such a simplification is valid. It is also enhanced by the fact that the load dynamics are much slower than the pressure dynamics, i.e. the small time variation of the much faster pressure dynamics have little effect on the load. According to the simplification above the flow rates in and out of the actuator are given by [11]

$$Q_A = Q_B = \frac{V_a}{\eta_{av}} \dot{\theta},$$

(2.12)

where $\eta_{av}$ is the volumetric efficiency. This volumetric efficiency only takes the leakage between side A and B into account, leakage back to the reservoir is not considered. From Fig. 2.2 it can be stated that the flows $Q_A$ and $Q_B$ can be expressed as

$$Q_A = Q_2 - Q_1 \quad \text{and} \quad Q_B = Q_4 - Q_3,$$

(2.13)

where $Q_1$ through $Q_4$ are linearized flows and can be expressed as

$$Q_1 = \frac{1}{2} Q_{1o} + K_{q1} x + K_{c1} (P_A - P_r)$$

$$Q_2 = \frac{1}{2} Q_{2o} + K_{q2} x + K_{c2} (P_s - P_A)$$

$$Q_3 = \frac{1}{2} Q_{3o} + K_{q3} x + K_{c3} (P_s - P_B)$$

$$Q_4 = \frac{1}{2} Q_{4o} + K_{q4} x + K_{c4} (P_B - P_r)$$

(2.14)

In (2.14), $Q_{1o}$ through $Q_{4o}$ are the nominal flow rates through the valve at steady operating conditions. $P_A$ and $P_B$ are the pressure levels in transition lines A and B respectively, $P_r$ is the pressure level in the return line and $P_s$ is the level in the supply line. $K_{q1}$ through $K_{q4}$ are the flow gains for each flow respectively. $K_{c1}$ through $K_{c4}$ are the pressure flow coefficients.

$$K_q \equiv \frac{\partial Q}{\partial x} \bigg|_o$$

$$K_c \equiv \frac{\partial Q}{\partial P} \bigg|_o$$

(2.15)

If the flow gains $K_{q1}$ and $K_{q3}$ are considered, it can be stated [11] that these two constants are negative according to definition (2.15) and the fact that the flow areas for $Q_1$ and $Q_3$ decrease as the spool displacement $x$ increases (see Fig. 2.2).

If a nominal steady state condition for the valve is considered [11], the displacement of the valve is given by $x = 0$, as well as the volumetric flow into and
out of ports A and B being zero (see Fig. 2.2). Under these conditions certain constraints have to be met. The nominal pressures at ports A and B, $P_{A_o}$ and $P_{B_o}$ both have to equal $\frac{1}{2} \cdot P_{s_o}$ which is the nominal supply pressure. Further $P_r$ being the nominal reservoir pressure has to be zero. The following can be stated

$$P_{A_o} = P_{B_o} = \frac{1}{2} \cdot P_{s_o} \text{ and } P_r = 0 \quad (2.16)$$

Under the nominal pressures mentioned above, it can be stated that the nominal flow $Q_{1_o}$ through $Q_{4_o}$ have to be equal to one another. For the valve coefficients $K_{q_n}$ it can be shown that the absolute value is consistent [11] for $n = 1, 2, 3, 4$ (keep in mind that it was concluded that $K_{q_1}$ and $K_{q_3}$ are negative). It can also be stated that the pressure flow coefficients $K_{c_1}$ through $K_{c_4}$ are to be equal one another. Equation (2.17) below displays this.

$$Q_{1_o} = Q_{2_o} = Q_{3_o} = Q_{4_o}$$

$$K_{q_1} = K_{q_3} = -K_q, \quad K_{q_2} = K_{q_3} = K_q$$

$$K_{c_1} = K_{c_2} = K_{c_3} = K_{c_4} = K_c, \quad (2.17)$$

where $K_c$ and $K_q$ are coefficients for the entire valve. By combining (2.14) and (2.17), equation (2.13) can be rewritten and the linearized version of the hydraulic flow is obtained

$$Q_A = 2K_q x - 2K_c(P_A - P_{s/2})$$

$$Q_B = 2K_q x + 2K_c(P_B - P_{s/2}) \quad (2.18)$$

### 2.3 Modeling of the electro magnetic spool

Spool movement is controlled by the input current $u$. The valve has three operating conditions. It can be referred to as a 4/3 valve with 4 ways and 3 positions [17]. The valve is operated by solenoids and when a current flows through the coils a magnetic field is generated, providing an electromotive force so that movement is achieved. The motion of the valve, no matter of direction, is opposed by a spring. There is a spring on each side of the valve and these springs are at rest when the valve is centered in between them [17]. This state blocks the flow of fluid to all ports. In Fig. 2.4, A and B are the ports, P is the pump and T is the reservoir (or tank). If none of the solenoids S1 and S2 are active there is no connection between the ports A, B and the pump and the reservoir, i.e nothing happens. If solenoid S2 is active the valve is pushed to the right connecting A and pump, and also B and reservoir. If solenoid S1 is active the opposite occurs, A connected to reservoir and B connected to pump. To present this analytically the general equation for motion is considered

$$m\ddot{x} + \xi \dot{x} + \kappa x = u, \quad (2.19)$$

where $m$ is the mass of the valve, $\xi$ is a constant that corresponds to friction and $\kappa$ is the coefficient of the springs, assuming that the springs are identical, and $x$
2.3. MODELING OF THE ELECTRO MAGNETIC SPOOL

Figure 2.4. The possible operating conditions of a 4/3-valve [17]. If the spool is centered no fluid flows through the actuator. The spool can connect port A to the pump and port B to the tank(reservoir) or the other way around.

is the displacement. According to (2.19) this system has 2 states, \( x_1 = x \) and \( x_2 = \dot{x} = \dot{x}_1 \), thus a second order transfer function. By applying Laplace theory the following transfer function is obtained

\[
x(s) = \frac{\frac{1}{m}}{s^2 + 2\frac{\xi}{m} s + \frac{\kappa}{m}} u(s)
\]  

(2.20)

To summarize, we have modeled the dynamics from input current \( u \) to spool position \( x \) (see (2.19)) and from flow \( Q \) to pressure \( P \) (see (2.11)). If we consider (2.14) we see that the spool position has been taken into account (for (2.11)) since the flows \( Q_A \) and \( Q_A \) depend on \( x \). In other words we have modeled the dynamics of the electro-hydraulic system from input current \( u \) to torque \( T \) (see (2.9)). By considering (2.19) and (2.11) it can be concluded that there are four states in the electro hydraulic system. The two pressure variables \( P_A \), \( P_B \) and the position and velocity of the spool, \( x \) and \( \dot{x} \). Our system can therefore be expressed as a fourth order transfer function. Such a transfer function where the system parameters are presented as \( a_n \) and \( b_n \) is seen below

\[
\tau_{\text{hyd}}(s) = \frac{b_3 s^3 + b_2 s^2 + b_1 s + b_0}{a_4 s^4 + a_3 s^3 + a_2 s^2 + a_1 s + a_0} u(s)
\]  

(2.21)

It is now a matter of identifying these parameters \( a_n \) and \( b_n \).
Chapter 3

Identification

This chapter explains the methods used for identification based on the model structure obtained in the previous chapter. Throughout this entire work a sampling interval of $h = 0.001\text{s}$ has been used. This depends on the reading rate of sensors. Generated input data throughout this work has been shaped according to sinusoidal signals, mainly because real drivers move the rotator in such patterns. All data shown in this work has been obtained using the real rotator, i.e we use no data from simulation.

3.1 Identification of system dynamics

Consider case I where only position is measurable and that the input to the mechanical system is current (see Fig. 1.1), not pressure. We identify a model from current to position. Since this lumped model does not only describe the dynamics of the true mechanical subsystem it is referred to as the model of the rotator from current input to position output.

Consider the mechanical model described in (2.8). Assuming ideally that the control signal $u$ is the input to the mechanical plant, then

$$J_u \cdot \ddot{\theta} = u - b_u \cdot \dot{\theta} - \tau_{\text{Coulomb}} u \cdot \text{sgn} (\dot{\theta})$$

models the dynamics of such a system. In (3.1) disturbances are not considered. This assumption neglects the electro-hydraulic part of the crane.
3.1.1 Determination of parameters for Coulomb friction

As mentioned in Chapter 2, $F_C$ corresponds to the Coulomb friction force. The friction levels can be determined by slowly increasing the current signal until movement. The method used is a bit different but follows the same idea. Instead of manually increasing the signal an open loop signal, e.g. a sinusoidal signal, is applied as input to the crane. The open loop signal used as input to the crane together with the response from the magnetic sensor were recorded and saved for analysis, see Fig. 3.1 To determine the lower and upper limit of the Coulomb friction (see Fig. 2.1.a) the moment of change for $\theta(t)$ is observed, for positive and negative change respectively. Fig. 3.1.a shows a negative change in position around the time 2 seconds. The magnitude of the reference signal at the same time corresponds to the negative friction constant $F_{Cn}$. Since the reference signal is current we can determine the magnitude of the current needed for the system to move. The positive constant $F_{Cp}$ is determined in the same way with the exception that positive position changes are observed. Input trajectories with different amplitude and frequency generated the values in Table 3.1. Since only one value can be used for each constant the mean is chosen.

3.1.2 The model from reference to position

To complete the model, $J_u$ and $b_u$ have to be identified. Based on (3.1) a block model is created in Simulink according to Fig. 3.2. The Coulomb friction block applies $F_{Cp}$ when $\dot{\theta} > 0$ and $F_{Cn}$ when $\dot{\theta} < 0$. The Simulink model in Fig. 3.2
Table 3.1. Measured values for Coulomb friction

<table>
<thead>
<tr>
<th></th>
<th>( F_{cp} )</th>
<th>( F_{cn} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>capture1</td>
<td>0.4634</td>
<td>0.4356</td>
</tr>
<tr>
<td>capture2</td>
<td>0.4712</td>
<td>0.4445</td>
</tr>
<tr>
<td>capture3</td>
<td>0.4812</td>
<td>0.4513</td>
</tr>
<tr>
<td>capture4</td>
<td>0.4465</td>
<td>0.4503</td>
</tr>
<tr>
<td>capture5</td>
<td>0.4573</td>
<td>0.4402</td>
</tr>
<tr>
<td>mean value</td>
<td>0.4639</td>
<td>0.4444</td>
</tr>
</tbody>
</table>

Figure 3.2. Simulink model describing equation (3.4). The block denoted ‘coulombfriction’ applies \( F_{cp} \) or \( F_{cn} \) depending on the sign of the velocity that the block is fed with.

is used for estimation of velocity. At this early stage in the process temporary values for viscous friction, \( \hat{b}_u \), and inertia, \( \hat{J}_u \), are determined by using the System Identification Toolbox in Simulink [8].

3.1.3 Friction compensation

Having knowledge of \( \hat{b}_u \) and \( \hat{J}_u \) in the model makes it possible to determine \( b_u \) and \( J_u \). First of all friction has to be compensated and that is done using the following method [6]. In (3.1) which is also stated below

\[
\hat{J}_u \cdot \ddot{\theta} = u - \hat{b}_u \cdot \dot{\theta} - \tau_{Coulomb_u} \cdot \text{sgn}(\dot{\theta}),
\]

we add \( \tau_{Coulomb_u} \cdot \text{sgn}(\dot{\theta}) \) to the control signal \( u \). By doing this the last term disappears and we get a linear model. Compensation requires some knowledge of the velocity and it is therefore estimated using the model in Fig. 3.2. In Fig.
3.3 this model can be seen in closed loop with a PID controller. The subsystem

\[ J_u \Theta(s) s^2 = U(s) - b \Theta(s) s \]  
\[ \Theta(s) / U(s) = \frac{1 / J_u}{s \cdot (s + b_u / J_u)} \]  

which shows that the transfer function has a pole in \( s = 0 \) which makes it unstable from current to position. The unstable transfer function is stabilized by introducing feed-back action. A proportional controller \( K_p \) is used in the loop (see Fig. 3.4).

\[ G(s) = \frac{\Theta(s)}{U(s)} = \frac{1 / J_u}{s \cdot (s + b_u / J_u)} \]
The transfer function for the closed loop system from reference to position $G_c(s)$ is

$$G_c(s) = \frac{K_p \cdot G(s)}{1 + K_p \cdot G(s)} = \frac{\frac{K_p}{J_u}}{s \cdot (s + \frac{b_u}{J_u})} \frac{1 + \frac{K_p}{J_u}}{s + (s + \frac{b_u}{J_u})}$$

(3.6)

$$\iff G_c(s) = \frac{\frac{K_p}{J_u}}{s^2 + \frac{b_u}{J_u} \cdot s + \frac{K_p}{J_u}}$$

(3.7)

It is now convenient to run a few reference signals and capture the output positions, altering the gain $K_p$. The different values chosen for $K_p$ can be observed in Table 3.2.

<table>
<thead>
<tr>
<th>$K_p$</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$K_{p1}$</td>
<td>0.10</td>
</tr>
<tr>
<td>$K_{p2}$</td>
<td>0.16</td>
</tr>
</tbody>
</table>

### 3.1.5 Data Analysis

The data obtained (see Fig.3.5) in the previous section is together with Matlab used to determine the parameters $J_u$ and $b_u$. The method will be explained for
one of the datasets. For the other set only the results are presented since the same method is used. After minor manipulations of the data the frequency response of the input and output signals is obtained using the Discrete Fourier transform defined by [2]

\[
X(k) = \sum_{j=0}^{N} x(j) \cdot w_N^{(j-1) \cdot (k-1)}
\]

(3.8)

where

\[
w_N = e^{(-2\pi \cdot i) / N},
\]

and is in MATLAB denoted \texttt{fft}. The command returns the discrete Fourier transform (DFT) \(X\) of the vector \(x\), computed with a fast Fourier transform (FFT) algorithm [9]. The input signal is a signal built up from three sinusoids with different amplitudes and frequencies (see Fig. 3.5a) to resemble the movement pattern of real drivers. Three peaks are seen in the power spectrum (see Fig. 3.6). In order to, among many other things, avoid duplicate data due to properties of sensors a resampling is used. When the true angular position is between two magnets on the magnetic sensors the sensor interprets it as if the true position is still at the previous magnet. When the position changes from magnet 1 too magnet 2 the measured value remains according to magnet 1 until the true position reaches magnet 2. This means that all measured values between magnets are the same. This is also the reason of the stepwise response from the magnetic sensor. In addition to resampling, zero padding is implemented and trends are removed to simplify the analysis.

The identification of a parametric model is done to match the data. We have the knowledge that the system behaves like a second order transfer function (see (3.7)). The \texttt{pem} command in MATLAB [2] allows the user to specify (attributes) in what way the estimation should be carried out. It can either focus on prediction, simulation or a certain passband range. Many models with different attributes were tried and the model that matched data best was chosen. In Fig. 3.7 below
3.1. IDENTIFICATION OF SYSTEM DYNAMICS

**Figure 3.6.** The Power spectrum of the input and output signals for $K_{p2}$, with zero padding implemented.

the validation for the best, in the sense of fit, parameter estimation is shown. All estimated models tried were continuous and of second order. It is important to remark that the validation was made on data that was not used for estimation. The dataset was divided into two parts before the estimation began. The transfer function for the estimated model was found to be

$$G_{cK_{p2}}(s) = \frac{0.005833 \cdot s + 11.68}{s^2 + 6.612 \cdot s + 11.87}$$

$$G_c(s) = \frac{K_p}{s^2 + \frac{b_u}{J_u} \cdot s + \frac{K_p}{J_u}}$$

If it is compared to (3.7), also seen above, it can be observed that there is an extra term in the numerator. The term is very small in comparison to the constant term and is therefore neglected. The transfer function computed from the other data set can be seen below, the extra term is removed.

$$G_{cK_{p1}}(s) = \frac{28.11}{s^2 + 10.02 \cdot s + 26.88} \quad (3.9)$$

Table 3.3 shows the values for $J_u$ and $b_u$ for each data set. The average of the parameters obtained was set as final values. As seen in Table 3.3 the parameters vary slightly. This variation may depend partially on uncertainty in
Figure 3.7. The validation of the estimated model, based on $K_{p2}$-data. The model is fed with data not used for estimation and compared to real values observed in the crane.

Table 3.3. Obtained values for parameters $J_u$ and $b_u$

<table>
<thead>
<tr>
<th></th>
<th>$J_u$</th>
<th>$b_u$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$K_{p1}$</td>
<td>0.0084</td>
<td>0.0555</td>
</tr>
<tr>
<td>$K_{p2}$</td>
<td>0.0060</td>
<td>0.0601</td>
</tr>
<tr>
<td>mean value</td>
<td>0.0072</td>
<td>0.0578</td>
</tr>
</tbody>
</table>

sensors, but the main reason is most likely the influence from unmodeled dynamics. As mentioned in section (3.1.3) the parameters $\hat{J}_u$ and $\hat{b}_u$ were not permanent, now that we have defined more accurate values they are to be used in the friction compensation.

The mechanical model with inserted parameters is found to be

$$G(s) = \frac{138.8}{s \cdot (s + 8.02)}$$  (3.10)
3.2 Identification of the hydraulic system

The electro-hydraulic model (2.21) acquired in Chapter 2 is identified below. If we consider the block ‘Electro-Hydraulic System’ in Fig. 1.1 we can say that we are identifying the subsystem that has current as input and differential of pressure, i.e torque as output.

A step input with added noise is used as input to the real system in open loop. This is to excite the valve in order to reveal valve dynamics [13]. Since no compensation of nonlinearities is present at this state the input signal is shaped in a particular way. A simple experiment such as the one in section 3.1.1 is done to reveal the levels of dead zones (nonlinearities shaped as ideal relay) in the valve. The knowledge of these levels is used to set the amplitude of the step larger. Fig. 3.8 shows the step input and the measured torque (differential of pressure). The identification from here on is identical to the method used in the previous section. After some data manipulation, fourth order parametric models are matched to the data. The validation of the model with best fit is presented in Fig. 3.9. Note that the identified model has been compared with different data. The obtained transfer function is

$$G(s)_{ol} = \frac{20.79(s + 1.382)(s^2 - 82.98s + 3965)}{(s + 16.18)(s + 1.587)(s^2 + 17.91s + 1084)}$$  \hspace{1cm} (3.11)
Figure 3.9. The identified model for the hydraulic system is fed the same input signal as the true system (crane). The response from the model is compared with the measured response from the pressure sensors.
3.3 Closed loop identification for dynamics of mechanics.

In this section we identify the mechanical subsystem, i.e the block 'Mechanical System' in Fig. 1.1. Note the difference from section 3.1, where we neglected the hydraulic subsystem and current was input to the mechanical system. In this case we identify a system that has torque as input and angular position as output. Since torque is the input we need to provide a desired torque. It is therefore assumed that torque is controlled. It is also considered that we are working with a linearized system since nonlinearities are assumed compensated when controlling torque.

Same method for identification is used in this section as in previous sections, that is matching parametric models to data. (2.8) is rewritten to get

$$J_m\ddot{\theta} = \tau_{hyd} - b_m\dot{\theta}, \quad (3.12)$$

where $J_m$ is the coefficient for inertia, $b_m$ is the coefficients for viscous friction and $\tau_{hyd}$ is the torque provided by the hydraulic system.

The transfer function for this system is, as mentioned previously, unstable, the loop is therefore closed using a controller with a gain $K_p$. The closed loop transfer function is presented below

$$G(s)_{mech}c = \frac{K_p}{s^2 + \frac{b_m}{J_m}s + \frac{K_p}{J_m}} \quad (3.13)$$

The setup for data acquisition can be observed in in Fig. 3.10. The 'Mechanics' block is the system we want to identify. The encapsuled block is the controlled hydraulic system with compensation. The loop is closed with the gain $K_p$ for stabilization purposes. Since torque is controlled, the encapsuled block can be considered as 1 due to the fact that the output signal (torque) equals the input(current) of the encapsuled block. Since current and torque are considered the same in this case it is possible to consider the pseudo setup in Fig. 3.11.

The setup in Fig. 3.11 is very similar to the setup in Fig. 3.4, the only difference is that torque is controlled. A model from reference position to true position(measured by the magnetic sensor) is identified using the data in Fig. 3.12. Various sums of sinusoids are used to excite the system. The identification is conducted as previously by manipulating data and matching parametric models of second order. The transfer function for the open loop system is

$$G_o(s) = \frac{70.922}{s(s + 11.06)} \quad (3.14)$$
Figure 3.10. The setup for acquisition of data for identification of mechanical model in closed loop. The hydraulic system is assumed to be controlled why the encapsuled block can be considered as 1. The gain is used to stabilize the otherwise unstable mechanical plant.
3.3. CLOSED LOOP IDENTIFICATION FOR DYNAMICS OF MECHANICS.

Figure 3.11. The pseudo setup for acquisition of data for identification of mechanical model in closed loop. It is assumed that the hydraulic system does not affect the mechanical model. The system is stabilized using a gain.
Figure 3.12. Data for identification of the mechanical plant is obtained by using the setup in Fig. 3.11. (a) Acquired data with $K_p = 0.5$ (b), Acquired data with $K_p = 0.75$
3.4 Summary

In this chapter it has been presented how the identification has been done in the two different cases. At first, we deal with the identification of a lumped model, which does not consider the electro-hydraulic system. The identified model corresponds to case I. The second part of the chapter deals with identification relevant for case II. It is presented how the electro-hydraulic model as well as the mechanical model are identified. In this case the two models have been identified separately, and is in a way the opposite of what we do for case I. The friction phenomenon has also been covered in this chapter. It has been presented how friction is identified and compensated. The chapter also discusses unstability for transfer functions. The identified models of this chapter are used for control system design in the next chapter.
Chapter 4

Control System Design and Evaluation

In this chapter the steps of control design for each of the identified models is explained. All experiments are done on the real rotator, i.e no simulation results are presented. We present the control system structure for cases where following sensors are used

- only the magnetic sensor, case I
- pressure sensors and magnetic sensor, case II
- only pressure sensors, case III
- pressure sensors and camera, case IV.

For each case it is explained how tuning is conducted and the experimental results of each structure is presented.

4.1 Position Control

This section deals with control system design using only the magnetic sensor. A method is presented for the simplified case where the dynamics of the hydraulic part of the system is neglected(case I). For control system structure the identified model (3.10) is used together with classical PID controllers.

4.1.1 Control system structure

A problem that arises with this particular plant is the fact that dynamics change when a log is picked up. For such systems a variety of methods for control system design can be used, some of which are adaptive control and internal model control. In this thesis an alternative method has been used. As proposed in [14, 5] a Model Following Control (MFC-p) structure has been used for position control. The
main idea of the MFC-p is to force the system to act as the identified model (3.10) even when true dynamics change. In Fig. 4.1 the MFC-p structure is presented. The block denoted ‘Friction compensation’ (see Fig. 3.3) contains the identified mechanical model (3.10). Friction compensation is done by feed forwarding the output signal \( u \) from the block. The signal \( u \) is the result of a closed loop control of the model (see Fig. 3.3). The block also provides a model response ‘\( \theta_4 \)’ given a reference trajectory. 'PID control 2' corrects the error between that model response and the actual measured position (\( \theta_4 \) that comes from (2), i.e the crane), an error that depends on change in dynamics and process disturbances. The controller forces in other words the true measured position from the crane to become as the model output position. The other controller ('PID control') corrects the error between the reference trajectory and actual measured position, i.e it is driven by the process error. The two PID controllers are tuned first with Ziegler-Nichols and then manually until good tracking is acquired.

**Figure 4.1.** For position control of the rotator a MFC-p structure has been used. The structure can be divided into three parts. Friction is compensated using the identified model (3.10) in a feed forward term. The 'PID control' block is a classical PID controller that is driven by the process error. As a last step in the control structure an additional control loop is introduced. This loop corrects the error between the model output and the actual measured position in the crane.
4.2. TORQUE CONTROL

4.1.2 Experimental results

Fig. 4.2 shows the tracking of a sum of sinusoids as reference signal. The resolution of the magnetic sensor is crucial here and one can see that it is not sufficient at some points but the setup tracks the reference signal satisfactorily. It should also be noted that the true position has a small delay in comparison to the reference trajectory, this depends on the fact that torque is not controlled. It is later shown that a controlled torque reduces this delay.

![Reference vs. Measured Position for MFC-p](image)

**Figure 4.2.** Tracking of a reference trajectory using the MFC-p structure. The position does not deviate much from the desired trajectory, the low resolution of the magnetic sensor can though be seen as the measured trajectory has a stepwise motion.

4.2 Torque Control

In this section the control system design for the hydraulic subsystem is presented. The identified model (3.11) is used for controller tuning.

4.2.1 Control system structure and controller tuning

A classical PID controller was tuned using the simulation model with the aid of optimization using the Control Design Toolbox in Simulink. The obtained controller was then implemented on the crane and tuned manually until appropriate
performance were achieved. The final gains for the PID were found to be

\[
K_P = 0.207 \\
K_I = 5.66 \\
K_D = 0.02
\]  

(4.1)

The control system setup is shown in Fig. 4.3. A reference trajectory is defined by user. Pressure sensors in the crane are used to close the loop. The PID controller corrects the process error. A feed forward term is used to compensate for non-linearities.

![Figure 4.3](image)

**Figure 4.3.** The setup used for control of the normalized torque. The feed forward term is used to compute the control signal for compensation of nonlinearities. The PID controller corrects the error between the true measured output and the reference trajectory.

### 4.2.2 Experimental results

Tracking of the reference torque is displayed in Fig. 4.4. The hydraulic system normally has a very oscillatory response and it can be seen that very few such oscillations are present with the implemented controller. The spikes at the crests and the troughs depend on the fact that the valve has to move at these points. When the valve moves there is a certain settling time before the flow of hydraulic liquid has reached a steady state.
4.3 Cascade Control

In case II, where both pressure sensor and magnetic sensor are considered a cascade control is implemented. The control structure for torque above will be used here. For the mechanical part a control system design will be implemented using the identified model (3.14)

4.3.1 Experimental results

A better control of position is obtained by controlling both pressure and position instead of only position. If the torque produced using the MFC-p structure (see Fig. 4.1) is studied, it can be seen that even though the position tracking is quite accurate the torque behaves in a peculiar way (see Fig. 4.5c) at zero Pa (or $\dot{\theta}(t) = 0$). This is the point where we compensate for nonlinearities in the MFC-p setup, the transition from negative to positive velocity and vice versa is not handled well. Since the hydraulic system underlies a number of unknown nonlinearities, phenomena like these appear when torque is not considered. The consequences of this can also be seen in Fig. 4.5.a, where there is a slight delay for the measured position just after a velocity transition.

Figure 4.4. Tracking of the torque using setup in Fig. 4.3. The behavior around the crests and troughs depends on valve movement.
(a) Reference trajectory and measured position for position control setup

(b) Reference trajectory and measured position for Cascade setup

(c) Corresponding differential of pressure for data in (a). The behavior of the torque around zero velocity is due to the fact that torque is not compensated and results in undesired behavior at system transitions.

(d) Corresponding differential of pressure for data in (b). It can be seen that compensation is done for the hydraulic system transitions are handled well.

Figure 4.5. Measured position and torque is compared for the position control setup and the cascade control, given the same reference trajectory.
The same phenomenon does not appear in the case of cascade control. There is a small spike at the transitions, but that is expected since the nonlinearity is not known at zero velocity. This is most likely due to dead zones in the valve. For the position it can be seen in Fig. 4.5c that there is no delay such as in the case for the position control setup case I, i.e. better tracking.

### 4.3.2 Control system design

In a cascade control setup (see Fig. 4.6) the aim is to use pressure measurements to compute the actual torque generated by the actuator, also to reduce oscillations while stabilizing the desired torque along the motion. Since a compensation for nonlinearities is done for the hydraulic subsystem it can be considered that the mechanical system is linearized, i.e. we do no additional compensation. In Fig. 4.6 the outer loop computes the reference torque needed to execute the reference trajectory. The inner loop controller computes the input current to the servo valve to correspond to the torque reference. The controller used for torque is put in cascade with a feedback controller for the position according to the Simulink block models in Fig. 4.7.

![Cascade control setup](image)
Figure 4.7. (a) Cascade control scheme. The control setup for position has a feed forward term with the identified model for the dynamics of the mechanics. The torque is controlled simply with a PID, also present is the compensation for nonlinearities; (b) Scheme of the feed forward term. The mechanical model is controlled in closed loop with a classical PID controller. The signal $u$ is added to the control signal for position.
In Fig. 4.7.a the scheme for the cascade control can be observed. The position is controlled with the aid of a feed-forward term that can be seen in Fig. 4.7.b. The identified mechanical model (3.14) is used in closed loop with a PID controller tuned by optimization in simulations. The output of the feed forward term forms a big part of the control signal \( u \). The controller (PID control2) for position therefore has gains that are small. It does not have to correct the error that much since the feed forward term contributes based on identified model. Assuming a perfect model only the disturbances would be corrected by this controller. Since the control signal relies on the identified model, big disturbances in the output signal are avoided. Yet again the system is forced to act as the model, making the control system design more robust.

4.4 Bumblebee camera based control

It was found above that angular position can be controlled just by using position sensing (case I) and that performance can be improved by using both pressure and position measurements (case II). It is now in our interest to see what happens when the magnetic sensor is removed and replaced with the mechanical model for position observations (case III). Instead of using the magnetic sensor for feedback the mechanical model is fed with the measured torque response from the hydraulic system and generates an angular position that is used for feed back.

An initial experiment is done, where the magnetic sensor is replaced with the response from the identified mechanical model (see Fig. 4.8). Running this a drift of position is observed and the reference trajectory is not tracked very well. As can

![Diagram](image-url)
be seen in Fig. 4.9 the true position resembles the reference trajectory but only in shape, and the offset changes with time and the true position drifts. This is an expected phenomenon since the real system is replaced with an identified model. Even if we have a very good model it is not going to be equal to the true system. Also, a model does not consider disturbances that affect the true system. The main reason for the drift is the uneven behavior of the deadzones in the hydraulic subsystem. The main idea in this section is to correct the closed loop behavior using the camera, which corresponds to case IV. Cameras are cheap devices and do not require complex implementation. In this thesis a stereo camera of type Bumblebee has been tried. Computation of position based on camera images results in big delays. The time delay of the camera is estimated to 1 second based on simple experiments, but it varies depending on the hardware used (laptop). Time delay of that magnitude is huge and in its natural state the signal cannot be used for feedback. A prediction based on differential of pressure and camera values is computed. The predicted value is used to periodically initiate the mechanical model in Fig. 4.8 at the true position.

4.4.1 Prediction

Consider the identified mechanical model

\[
\text{Figure 4.9. In this experiment position is controlled without the use of any position measurements. With the aid of the magnetic sensor the position is compared to the reference trajectory. It can clearly be seen that the measured position drifts away from the reference trajectory.}
\]
when the model is transformed to discrete time with $T_s = 0.1\,s$, this gives

$$G_z(z) = \frac{0.2533z+0.1758}{(z^2-1.331z+0.3309)} = \frac{b_1z+b_2}{z^2+a_1z+a_2} = \frac{\Theta(z)}{R(z)}$$

which implies

$$b_1R(z) + \frac{b_2}{z}R(z) = \Theta(z)z + a_1\Theta(z) + \frac{b_2}{z}\Theta(z)$$

and

$$b_1r[t] + b_2r[t-1] = \theta[t+1] + a_1\theta[t] + a_2\theta[t-1],$$

After minor manipulations $\theta[t+1]$ can be extracted from (4.4.1), where $r[t]$ is the corresponding input to the system, i.e. the differential of pressure. The term is a prediction of the position 0.1 seconds later, remember that $T_s = 0.1\,s$. The term depends on a combination of old and present values of the true position (camera) and differential of pressure:

$$\theta[t+1] = b_1r[t] + b_2r[t-1] - a_1\theta[t] - a_2\theta[t-1]$$

The camera has a total delay of 1 second and so far only 0.1 seconds are predicted. A solution could be to increase the sampling time $T_s$ to 1.0\,s but that has not been done for several reasons. With big sampling time a lot of the dynamics covered by the model could be lost, also the method loses flexibility. If a scenario where the delay changes is considered the algorithm is easily changed in the case of small sampling period, neglecting one or several steps is easily done. The sample time of 0.1 seconds is kept and the prediction is made in 10 steps, where each step predicts 0.1 seconds ahead.

At a certain time $[\tau]$ the camera provides a position, the corresponding pressure measurements are read at $[\tau-10]$, further position is calculated at time $[\tau-9]$, that is used together with pressure measurements at time $[\tau-9]$ to calculate position at time $[\tau-8]$, and so on until $\theta[\tau]$ is obtained.

The measurements provided by the camera are not always reliable. The camera is easily affected by light, and even small changes in light can affect the reading in quite big ways. At startup the camera is calibrated according to the light in the room. If the light changes during measurements, the results might get invalid. The connection between the camera and the laptop is not ideal and in some cases it is not fast enough, which results in position estimation based on too few data. An average weighting with the corresponding output of the mechanical model has therefore been done in each step to try to prevent or at least minimize this error. An example is presented in Fig. 4.10, where a certain time instance, $t = 2.0$, is considered. At that point we have knowledge of $\Delta p(t)$ and $\theta(t)$, the output from
the mechanical model fed with $\Delta p(t)$, for all $t < 2.0$. $\theta_c(1.0)$, the value provided by the camera, is also known. $\Delta p(1.0)$ and $\theta_c(1.0)$ are inserted into (4.4.1) to calculate $\theta_c(1.1)$. That value is the weighted with $\theta(1.1)$ and then proceeded to the subsequent estimation box and so forth until $\theta_c(2.0)$ is acquired. As mentioned previously that value is used to initiate the mechanical model, which is used as feedback.

### 4.4.2 Experimental results

In Fig. 4.11 the tracking of a reference trajectory with the estimation implemented can be seen. An indication that drift still remains can clearly be seen, but it has decreased and in some parts there is no drift (still an offset though). It is hard to say exactly why the drift only decreased and was not entirely eliminated. The camera produces an angle with an uncertainty, i.e the same true angle can by the camera be apprehended as several different angles and that affects results a lot. Second it can be said that the delay is not entirely constant. An error of 10-15% can be expected from time to time. These factors and the fact that the estimation might not be perfect can contribute to a propagaton of a small error through time resulting in larger errors.
Figure 4.11. Tracking of the angular position using camera. A drift remains even though the prediction to compensate the delay is used. The drift has decreased and is in some intervals not present.
4.5 Summary

In this chapter we have discussed the control system design for the four cases. It is initially presented how an MFC-p setup is used for tracking of angular position in case I. The evaluation indicates that such control structure is sufficient for controlling the angular position when only the position itself is measurable. Further, for case II it is presented how torque is controlled. The controlled torque is used to form a cascade control design together with a position controller. We compare the results for the two first cases and conclude that a better tracking of the position is obtained when torque is controlled (case II). The second part of the chapter covers case III and case IV. A simple experiment shows that tracking of position is not possible in case III. When the camera is introduced, an additional problem of delay arises. To deal with the delay a prediction is implemented. In general it can be said that results were not sufficient in case IV even though we saw an improvement.
Chapter 5

Conclusion and Future Work

This chapter aims to answer the questions posed in this thesis as well as propose possible future improvements that can be implemented.

5.1 Conclusion

- If we consider case I. For an electro-hydraulically actuated rotary system, where pressure is not measurable but angular position is, it can be said that such a system can be controlled sufficiently well. The controller implemented in this thesis is not the most advanced but it is still able to track various reference trajectories. One must keep in mind that we are trying to adjust the position so that a log and not a needle can be gripped. Minor errors that depend on assumptions done during identification are visible but do not prevent the crane from executing desired tasks.

- In the case where both pressure and position can be measured, that is case II, the cascade control setup results in good tracking. The method manages to prevent errors where the previous setup fails. We can conclude that the cascade setup is sufficient for a much more accurate control of the angular position. It is though important to mention that cascade control with PID:s and feed forward terms is the only method tried in this thesis and there are many other methods that may result in even better results. We can conclude that it is sufficient when applied to systems, such as the one used in this thesis.

- In case III it can be concluded that the work done in this thesis is not sufficient for control of the angular position just by using pressure measurements. The shape of the reference trajectory is well resembled but a huge problem with drift still remains. The torque provided from the hydraulic system should ideally result in the desired position but a model never coincides exactly with the true system and the method therefore fails.
• Unfortunately in case IV the prediction method did not work out as planned. As previously the shape of the reference trajectory is maintained but the full elimination of the drift was not obtained. It can be said that the implemented solution is not sufficient, but still manages to decrease the drift a bit. These results do not answer the question weather or not a camera can successfully be used for feedback action, it can just be concluded that this particular solution with this particular camera and algorithm can not.

5.2 Future Work

For future work it should be considered to try different sensing devices. The camera and its algorithm used in this thesis are too slow. If no sensor can be mounted on the rotator different cameras ought to be tried. As an alternative an improvement of the algorithm can be sufficient to reduce the delay. In addition it should be considered to run the camera on the same hardware as the rest of the application to avoid unnecessary delay.

As for prediction, Kalman filtering should be implemented to see if this results in better estimation. Still the main concern for future work should be to reduce the delay.

Further, solutions where the inertia of the mechanical part is considered variable could be tried. When logs are picked up the inertia changes. Different methods for identification can be applied and result in more accurate models.

The crane is a challenging system for implementation and tests of different methods, since many different subsystems with unique physical properties are present.
Bibliography


