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# Testing and implementation of a backlash detection algorithm

Max Haventon  
Jakob Öberg

Department of Automatic Control  
Lund University  
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<i>Author(s)</i> Max Haventon and Jakob Öberg		<i>Supervisor</i> Christian Schwertdt ABB in Malmö Tore Hägglund Automatic Control (Examiner)	
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<i>Title and subtitle</i> Testing and implementation of a backlash detection algorithm. (Test och implementering av en glappdetekteringsmetod)			
<i>Abstract</i> Backlash is a well documented and rather common non-linearity which is present in most mechanical and hydraulic systems. The amount of backlash varies depending on the dynamics of the system, for example a gear box in a car needs some space for heat expansion and consequently some amount of backlash in order to function. It is of interest to detect and estimate the amount of backlash automatically, since the time between the manual inspections often is long. This thesis covers the method described in "Automatic on-line estimation of backlash in control loops" written by Tore Hägglund and published in the Journal of Process Control in January 2007. One of the main objectives of this master thesis is to extend the safety net to guarantee the robustness of the backlash estimation procedure described in the article. The purpose of the safety net is to make sure that backlash estimates are only calculated when the system behavior resembles backlash. Conditions for period time, curve form and setpoint are discussed and investigated. The backlash estimation procedure is implemented as a control module in a prototype library in ABB Control Builder, a software used for PLC programming in an ABB 800xA environment. Finally, industrial field tests are performed to confirm the robustness of the method.			
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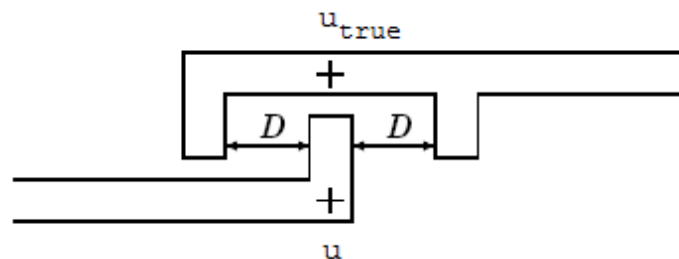
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# 1. Introduction to backlash

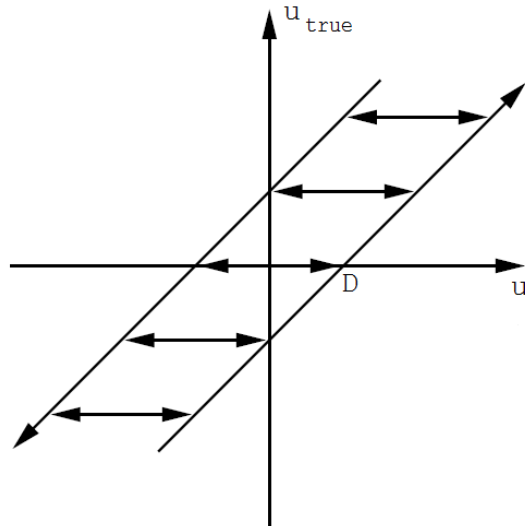
Backlash, or *glapp* in Swedish, is a well documented and rather common non-linearity which is present in most mechanical and hydraulic systems. Backlash appears whenever two physical parts are supposed to move together and there is an amount of space between the parts. Some systems or parts must have some amount of backlash in order to function, for example a gear box in a car needs some space for heat expansion. Other systems and components are free from backlash when new, but after some time in use the wear results in an introduction of backlash in the system. In general the amount of backlash increases with time and wear, regardless of how much backlash was present when the component was new.

When backlash is present in a control loop, the system can be in two modes; in contact or not in contact. Figure 1.1 shows a simple sketch of a mechanical two-part system where backlash is acting between the parts. It is assumed that the backlash is acting between the controller and the process.



**Figure 1.1** – Sketch of backlash in a mechanical system [1]. Note that the size of the backlash equals  $2D$  in this sketch.

When the control signal is constantly changing in one direction, for example increasing, the parts will be in contact and have no effect on the system what so ever. The problem arises when the control signal,  $u$ , changes direction, in this case from increasing to decreasing, since it then has to pass through the gap of the backlash, or the *dead band*,  $d$ . While  $u$  is drifting through the dead band, the backlash is not in contact, and the output from the backlash,  $u_{true}$ , remains constant until contact is made at either end. The signal  $u_{true}$  is the part of the control signal that is actually carried through to the process, while  $u$  is the output from the controller. The relation between  $u$  and  $u_{true}$  can be observed in figure 1.2.



**Figure 1.2** – Input-output characteristics of backlash. Arrows indicate possible directions in each section [1].

In figure 1.2, the diagonal lines represent contact, while the horizontal ones show how  $u$  drifts through the gap. For a change in direction, the dead band must be passed. Notice that  $u_{\text{true}}$  is constant along the horizontal lines.

## 1.1 Closed loop stability

In this and the following section, it is assumed that the reader is somewhat familiar with non linear methods of analysis, such as the circle criterion and the field of describing function analysis. For the less academic reader, these sections are safe to skip.

The input-output characteristics of a backlash can be described analytically as

$$\begin{cases} \dot{u}_{out} = \dot{u}_{in} , & \text{when in contact} \\ \dot{u}_{out} = 0 , & \text{otherwise.} \end{cases}$$

If this model is used, it is possible to analyze the stability of the closed loop system using the small gain theorem and other non-linear control conditions for stability. The gain from  $\dot{u}_{in}$  to  $\dot{u}_{out}$  is  $\leq 1$ , which means that the closed loop system is asymptotically stable if, see [1],

$$|P(i\omega) \cdot C(i\omega)| < 1, \quad \text{for all } \omega.$$

Note that it is possible to use the time derivative of  $u$  instead of  $u$  itself by imagining a derivative on the backlash input/controller output and an integrator on the backlash output/process input. As these cancel each other out, no changes need to be made to the continuous system.

A more detailed analysis of the stability can be made using the circle criterion. The relation between  $\dot{u}_{in}$  and  $\dot{u}_{out}$  from above has a gain between zero and one, which means that the circle is bounded by

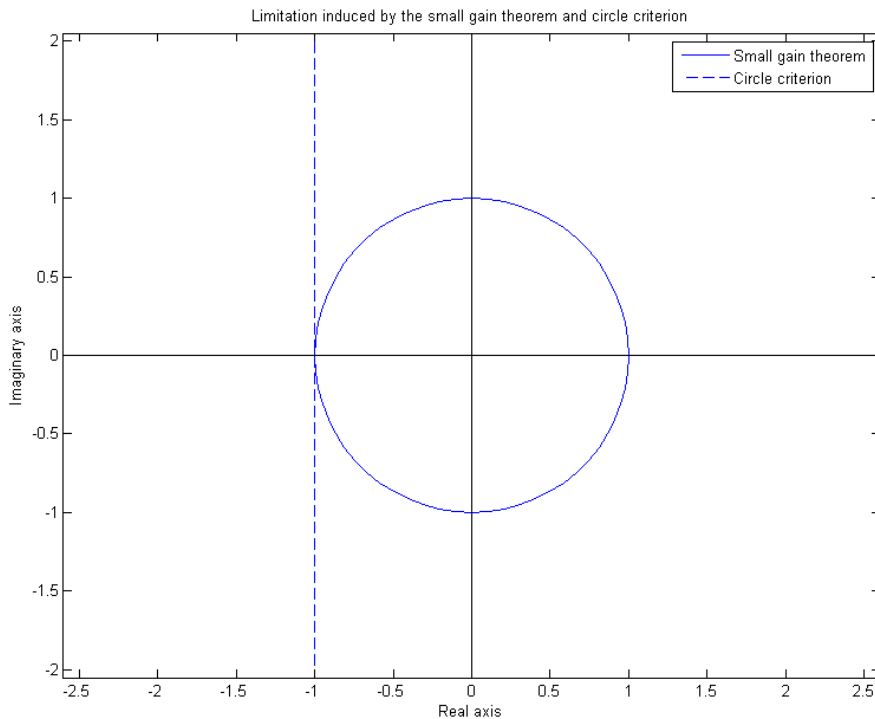
$$k_1 = 0 \rightarrow \frac{-1}{k_1} = -\infty$$

$$k_2 = 1 \rightarrow \frac{-1}{k_1} = -1.$$

From this it follows that the bound

$$\operatorname{Re}(P(i\omega) \cdot C(i\omega)) > -1, \quad \text{for all } \omega,$$

guarantees closed loop stability. This condition for stability is obviously less restrictive than the small gain theorem, but still rather restraining. The stability areas given by the small gain theorem and circle criterion are shown in figure 1.3.

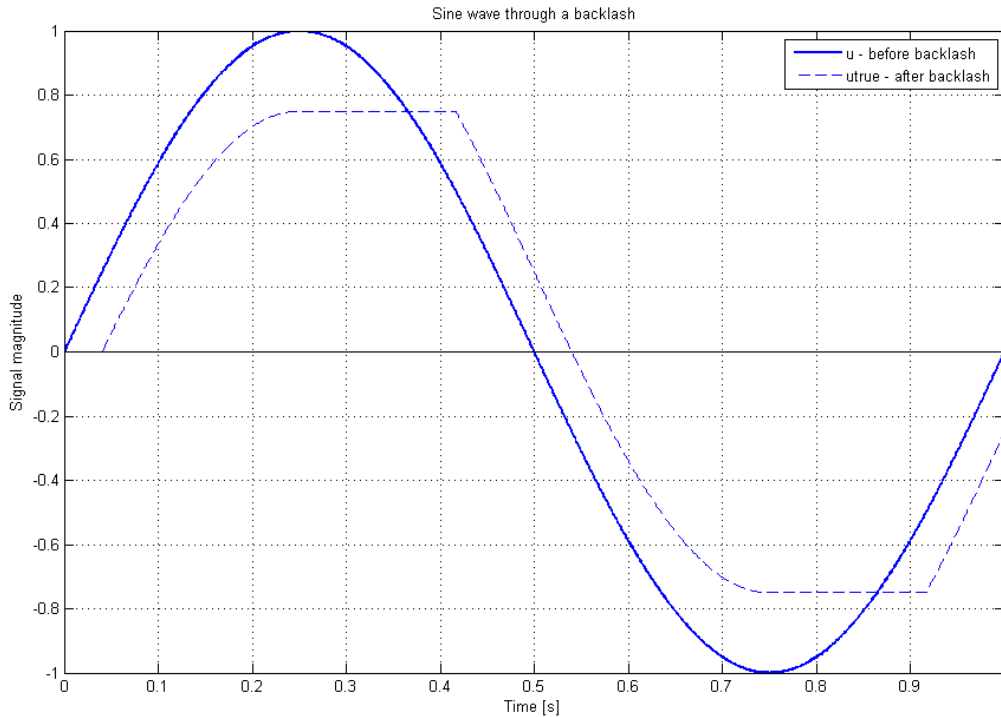


**Figure 1.3** – *S-plane limitations on the open loop Nyquist curve.*

## 1.2 Existence of limit cycles

In section 1.1, it was shown that stability is guaranteed for all closed loop systems with backlash as long as the continuous part of the system,  $P(i\omega) \cdot C(i\omega)$ , stays to the right of the line  $\operatorname{Re}(i\omega) > -1$  in the  $s$ -plane. Simulations show that this condition is a bit too restrictive, backlash rarely makes stable systems unstable. A more common effect caused by backlash is limit cycles. Limit cycles can be predicted using describing function analysis [2].

The describing function of a backlash can be derived from figure 1.4, where a sine wave is fed through a backlash, and the output is observed.



**Figure 1.4** – A sine wave is used to derive the describing function  $N(A)$  for a backlash block.

From figure 1.4 the describing function can, according to [4], be calculated as

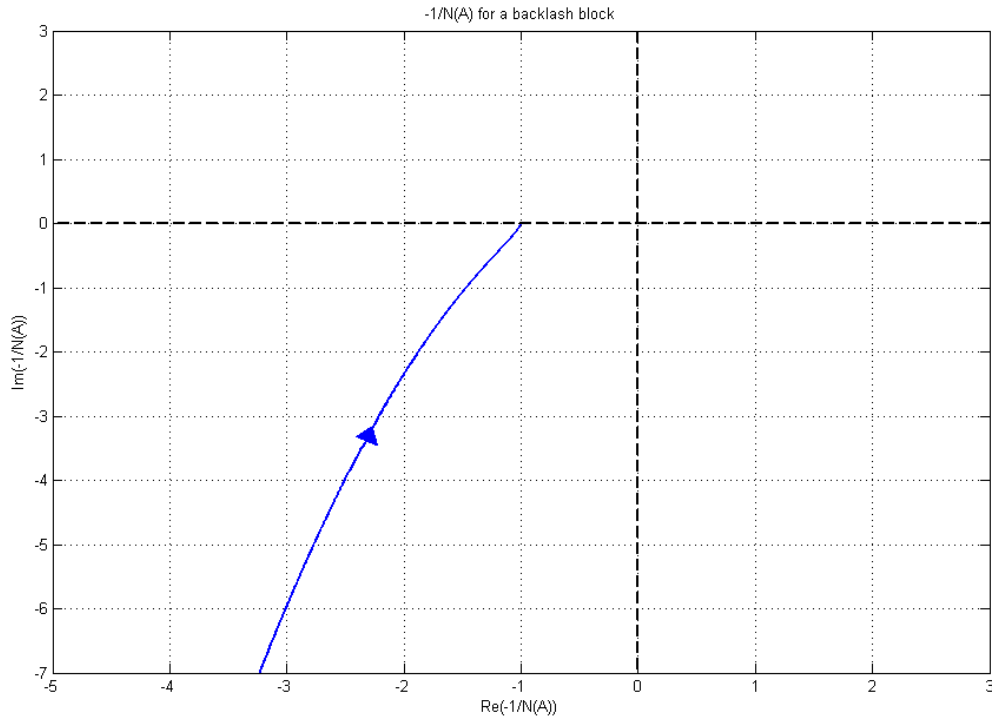
$$N(A, d) = \frac{1}{\pi} \left( \frac{\pi}{2} + \arcsin\left(1 - \frac{d}{A}\right) + \left(1 - \frac{d}{A}\right) \sqrt{\frac{d}{A} \left(2 - \frac{d}{A}\right)} - i \frac{d}{A} \left(2 - \frac{d}{A}\right) \right).$$

This describing function has several interesting properties. Since  $\arcsin(x)$  is only defined for  $-1 < x < 1$ ,  $A$  must be at the very least  $d/2$ . This means that the describing function is only defined for amplitudes larger than half the dead band. Of course, for smaller amplitudes, the output from the backlash block would be constant, as the dead band is never passed. Secondly, the dead band does not occur in the equation without being divided by  $A$ . As a consequence, a change in  $d$  does not alter the shape of the describing function, it only affects what amplitude corresponds to what point on the curve. That is:

$$N\left(A, \frac{d}{c}\right) = N(cA, d).$$

Limit cycles appear when the Nyquist diagram of the continuous system,  $P(s) \cdot C(s)$ , intersects the negative inverse of  $N(A, d)$ . The limit cycle oscillation is then predicted to be of frequency  $\omega$ , and amplitude  $A$  [2].

Figure 1.5 shows the negative inverse of a describing function of a backlash.



**Figure 1.5** – The negative inverse of the describing function of a backlash, regardless of the size of the dead band. The curve converges to -1 with increasing amplitude  $A$ . Compare with figure 1.4.

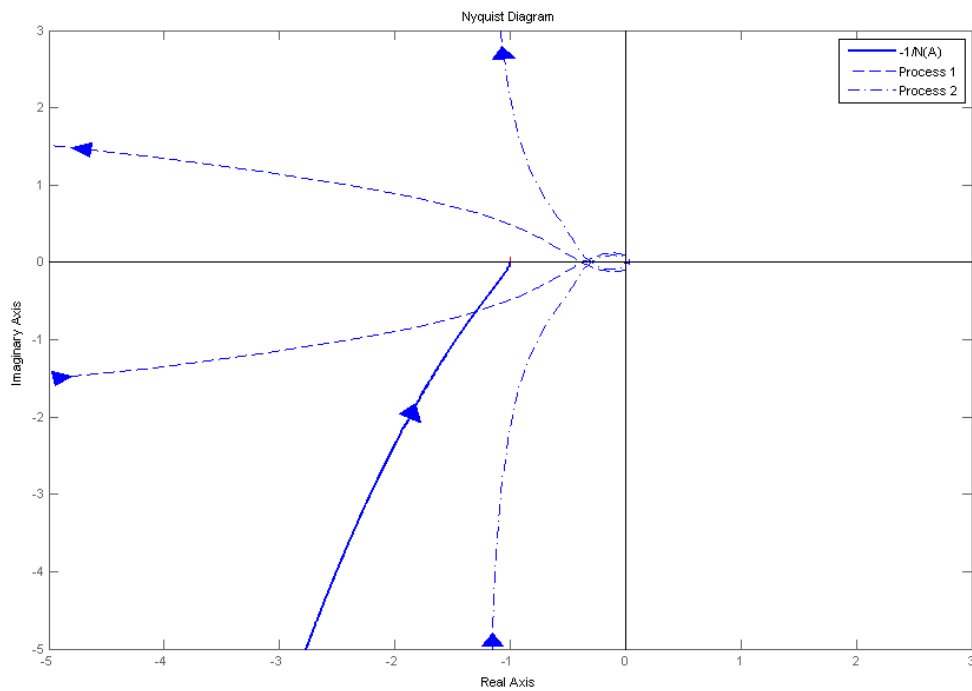
Obviously, all closed loop systems that satisfy the small gain theorem or circle criterion from above avoids limit cycles. One set of closed loop systems that does not avoid intersection with  $-1/N(A)$  is integrating processes controlled with PI-/PID-controllers. Figure 1.6 shows the Nyquist-plots for

$$P_1(s) = \frac{1}{s(1 + 0.8s)} e^{-0.2s},$$

and

$$P_2(s) = \frac{1}{(1 + 0.8s)^4},$$

both controlled with PID-controllers [3]. The process values have been filtered through second order low pass filters in the feedback loops, which is included in the analysis of the continuous system.



**Figure 1.6** – Nyquist plots of process  $P_1$  and  $P_2$  controlled with PID-controllers and low pass filtered in the feedback loop. The intersection between  $-1/N(A)$  and the Nyquist diagram for process  $P_1$  indicates that a limit cycle is likely to occur.

Figure 1.6 shows that the integrating process controlled with a PID-controller gives rise to a limit cycle. As mentioned above, the size of the dead band  $d$  does not change the shape of the describing function. This means that the limit cycle's frequency will be independent of the dead band [4].

## 2. Background and related work

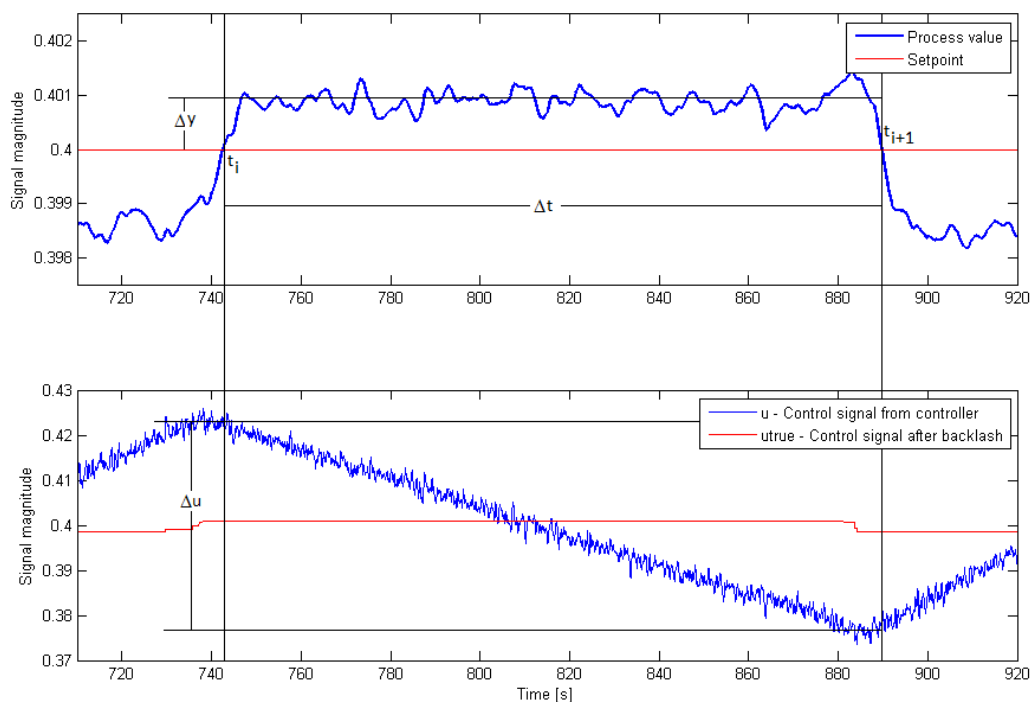
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*This master thesis is heavily based on the article “Automatic on-line estimation of backlash in control loops” [4], written by Tore Hägglund and published in the Journal of Process Control in January 2007. This chapter describes the backlash estimation and compensation method in the article, which provides an introduction to findings and results later in this thesis. How to detect and estimate the amount of backlash automatically and consequently compensate for the dead band based on normal operating data, is also explained in this chapter.*

---

### 2.1 Backlash estimation

It is of interest to detect and estimate the amount of backlash automatically, since the time between the manual inspections of control loops is often long. The estimation is done based on normal operating data and without any knowledge of the process, except for the static process gain, or other support provided by the operators.



**Figure 2.1** – Typical backlash behavior in process value and control signal.

Typical backlash behavior is shown in figure 2.1, where the noisy process output  $y$  has been filtered through a second-order low-pass filter,

$$Y_f(s) = \frac{1}{(1 + sT_f)^2} Y(s).$$

The filter, with filter-time constant  $T_f = T_d/5$ , or  $T_f = T_i/10$  for PI-controllers, is used to remove higher frequency components such as noise from the process value before backlash estimation is performed. Figure 2.1 shows how a controller having integral action controls a stable process when there is backlash in the control loop. When the control signal  $u$  drifts through the dead band caused by the backlash, a typical signal shape can be seen when the process output remains a distance  $\Delta y$  from the setpoint. The process output stays this way and is not controlled towards the setpoint until the control signal has changed an amount  $\Delta u$ . The two crossings on the setpoint axis are marked  $t_{i_1}$  and  $t_{i+1}$  in the figure and the time between these zero crossings is denoted  $\Delta t$ . When online, zero crossings can be detected by observing whether the error has changed sign since the last sample, that is

$$e(t) \cdot e(t - h) \leq 0 \rightarrow \text{zero crossing} \quad (2.1)$$

The change  $\Delta u$  of the control signal is mainly caused by the integral part of the controller, which is discussed more explicitly later in this thesis. The change of the control signal can be written as

$$\Delta u = \frac{K}{T_i} \int_{t_i}^{t_{i+1}} |e| dt = \frac{K}{T_i} \Delta y \Delta t .$$

This is exactly true for PI-controllers, but an approximation for PID-controllers since the derivative part is neglected. The approximation can be done since the derivative part is small; this is shown in section 7.5. The distance from the process output to the setpoint is

$$\Delta y = \frac{\int_{t_i}^{t_{i+1}} |e| dt}{\Delta t} . \quad (2.2)$$

The relation between the process output and the control signal, where the backlash is closed and the mechanical parts move, is mainly determined by the static process gain  $K_p$ :

$$\Delta y = K_p \Delta u_{true} , \quad (2.3)$$

where

$$\Delta u = \Delta u_{true} + d .$$

From the equations above the following expression for estimating the backlash can be obtained

$$\hat{d} = \Delta u - \Delta u_{true} = \frac{K}{T_i} \Delta y \Delta t - \frac{\Delta y}{K_p} . \quad (2.4)$$

Since the backlash estimator, defined by equation (2.4), assumes that the signals change slowly it is of interest to verify this before the estimation is performed. A way to do this is to see if  $\Delta t$  is long compared to  $T_i$ , which in turn is proportional to the closed loop time constant [3]. The exact value when  $\Delta t$  is long is determined later in this thesis in section 5.2.

To estimate the backlash online, the controller parameters  $K$  and  $T_i$  must be known. Additional information needed is  $\Delta y$ , the static process gain  $K_p$  and the time  $\Delta t$  between zero crossings, but note that access to the control signal  $u$  is not necessary. The controller parameters are always known, and depending on how the backlash estimator is implemented they might be directly accessible.  $\Delta y$  and  $\Delta t$  can both be calculated online, according to equation (2.1) and (2.2), meaning

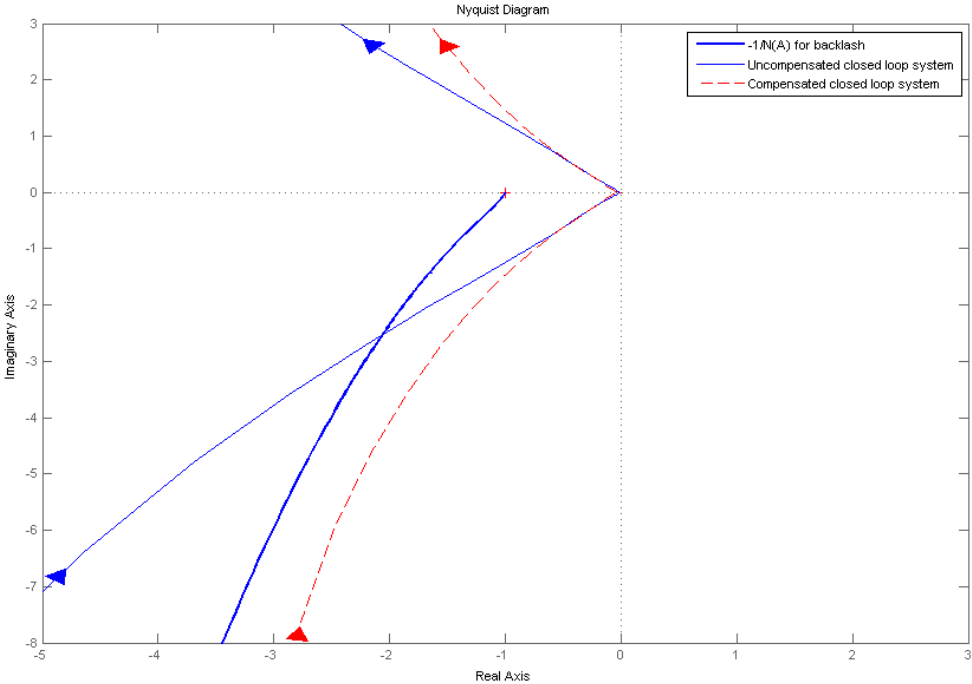


that the only potential unknown is the static process gain. How the knowledge of the process gain affects the method is analyzed thoroughly in section 7.2

## 2.2 Backlash compensation

It is of interest to replace or repair parts of the mechanics as the backlash deteriorates the control performance during operation. Because the amount of backlash normally increases with wear, this is even more important. To avoid stopping the production and for other economical reasons it is valuable to use the parts for as long time as possible and consequently compensate for the backlash.

There are several ways to compensate for a backlash. With linear control design, oscillations due to backlash can be removed by introducing a phase lead compensator. The filter prevents the two curves in the Nyquist diagram to intersect and consequently the oscillations are removed. The Nyquist diagram in figure 2.2 shows how an integrating process is filtered through a phase lead compensator and avoids an intersection with the negative inverse of the describing function of a backlash.



**Figure 2.2** – The oscillations due to backlash can be removed with a phase lead compensator.

A phase lead compensator is useful if limit cycles due to backlash occur in the control loop, but it does not eliminate typical backlash behavior from the process value.

Another way to compensate for the backlash is to “jump” through the gap every time the control action is reversed, a backlash inverse compensation. If this is done with perfection, the backlash does not affect the closed loop system in any way. By adding a compensation-signal to the feed forward input of the controller every time the control signal is reversed the compensation can be done. The controller output  $u$  then consists of the feedback term  $u_{FB}$ , which is the control signal calculated by the PID-algorithm, and the feed forward compensation part  $u_{FF}$

$$u = u_{FB} + u_{FF} ,$$

where the compensation for an ideal backlash is

$$u_{FF} = \frac{d}{2} \text{sign} \left( \frac{du}{dt} \right).$$

In reality this compensation would not work since the noisy environment distorts the time derivative of the control signal. Filtering the control signal before taking the derivative, as

$$u_{FF} = \frac{\delta}{2} \text{sign} \left( \frac{du_f}{dt} \right),$$

is a possible modification. The filtered control signal is denoted  $u_f$  and the compensator  $\delta$  is a value smaller or equal to the true dead band, because of the filter. The detection of when the control signal is reversed is delayed by the filter, which means that the signal already has started its way through the backlash when the detection takes place. A full dead band compensation will therefore result in an over compensation.

Another approach that is used in this thesis is based directly on the measurement signal with the feed forward

$$u_{FF} = \frac{\delta}{2} \text{sign}(e).$$

The control error  $e$  is the difference between the setpoint and the filtered process value. When the control signal is reversed, so is the sign of the control error  $e$  and the approach can therefore be used. As the error is based on the filtered process output, the sign does not change too rapidly.

## 3. Project description

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*Everything accomplished in the thesis is more or less directly connected to the article “Automatic on-line estimation of backlash in control loops” [4]. This includes analysis when things were not instinctively clear, improvements when needed, extensive testing and implementation in a commercial control system.*

---

### 3.1 Project goals

When developing solutions for industrial use, reliability and functionality must be guaranteed regardless of operating conditions. Especially in the case of an automatic procedure that is to run unsupervised, stability is crucial. If the product fails to live up to the customers’ expectations, the developing company loses in credibility to competitors. In [4] it is stated that:

*“To obtain a robust procedure that is automatic in the sense that no user interaction is needed, more industrial field tests have to be performed, and it is likely that the supervisory net must be extended.”*

This quote defines two of the project goals, namely:

- What parts of the safety net are sufficient, and what needs to be extended or added to guarantee robustness against system alterations?
- Additional industrial testing must be done.

In addition to these fundamental goals that focus on the detection method itself, we added some that concern the implementation and customer experience:

- What functions are interesting to customers?
- How should the method be implemented; stand-alone or a part of a controller?
- What limitations on processes, controller and operating conditions are present?

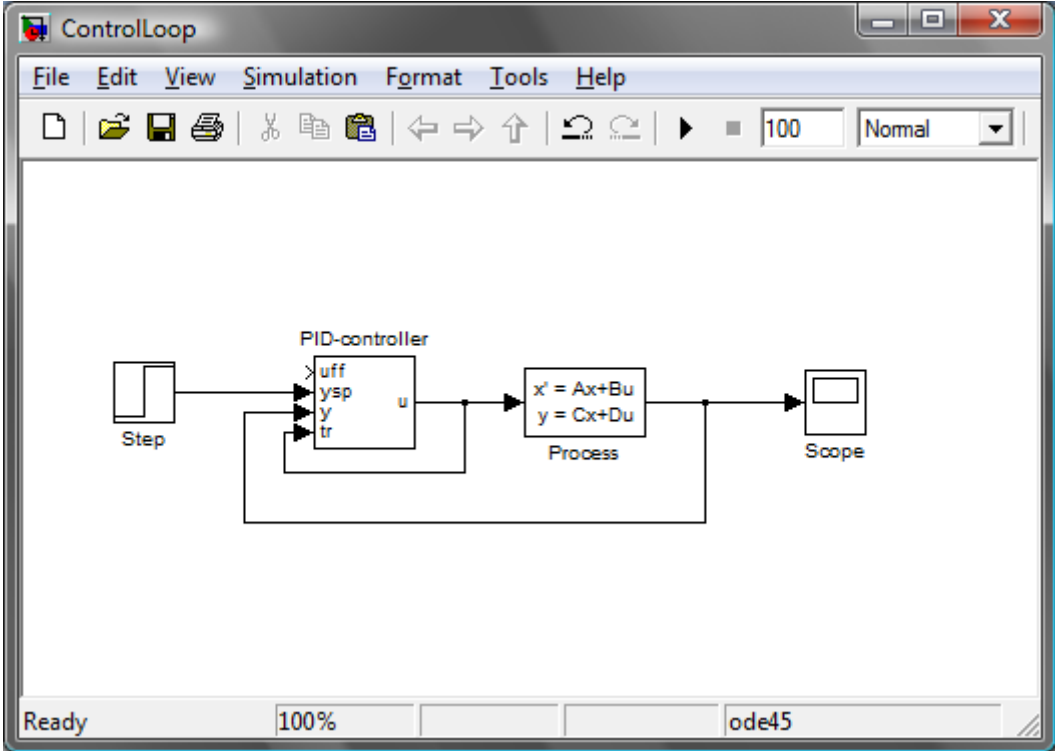
### 3.2 Method

When we were handed this project we knew little of the backlash phenomenon. Before trying to analyze the method described in [4], on which this master thesis depends, we needed to understand the effects of backlash. Simulation was crucial at this stage, and the first three weeks we did almost nothing but simulations using the MathWorks MatLab and Simulink software.

When we began understanding the concept of backlash we moved on to the backlash estimation procedure. The method was thoroughly examined and tested before we decided it was time to proceed with the implementation part of the project. The implementation basically meant translation from MatLab script to the Structured Text (ST) programming language, which is an IEC 61131-3 dialect for Programmable Logic Controller (PLC) programming.

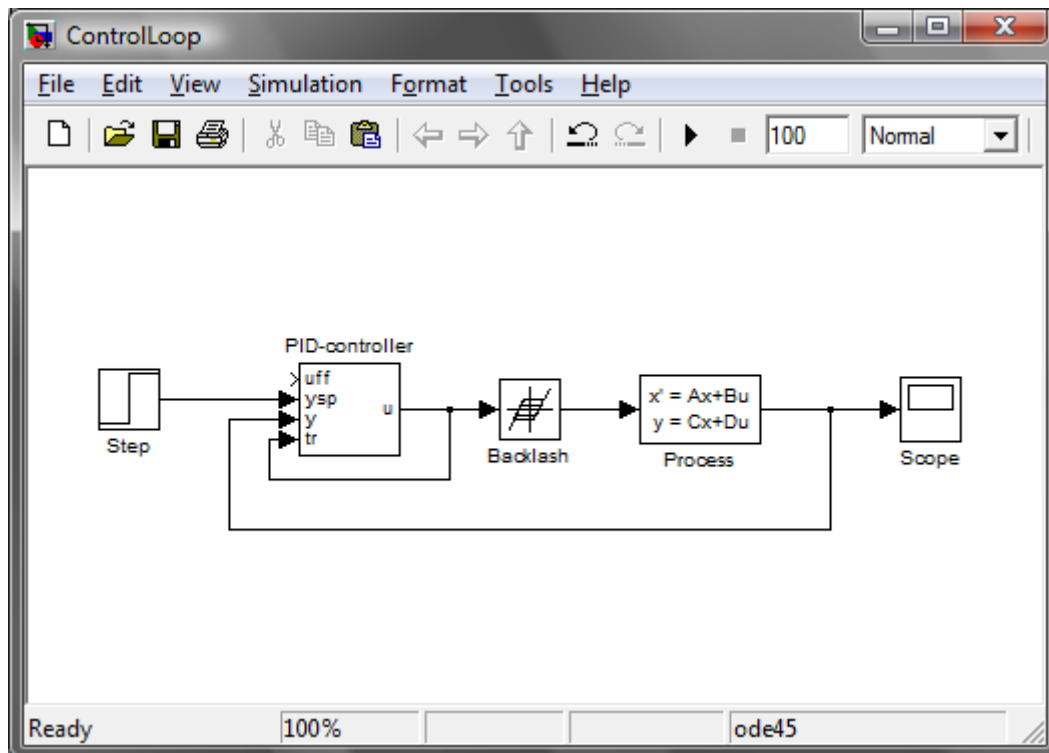
### 3.3 Simulink simulation

Simulink is a graphic simulation environment based on MatLab, both developed by *The MathWorks Inc.* Simulating a control system in Simulink is very intuitive; one simply selects the components needed from the library and connects them in a block schedule kind of way. See figure 3.1 for an example of a simple control loop.



**Figure 3.1** – A simple control loop in the Simulink environment.

The Simulink library contains a wide selection of components that are ready to be inserted into the model. One of these is, fortunately, the backlash block. Adding the backlash block to our simple model yields the extended model in figure 3.2, which is a simplified version of the simulation model we have been using throughout this master thesis.



**Figure 3.2** – A simple control loop with backlash acting on the process input.

Simulink is not a real time simulator, meaning that no interaction with the system can be made during operation since the time scale is changed. This is most often a great advantage, as a simulation of several thousand seconds can be performed in less than 10 seconds. It can however also be a disadvantage, as we are investigating and implementing a method for online backlash detection. This was never much of a problem though, as the method does not interact with the system, it merely observes and detects. Therefore, the simulation could be done first, separately, and the estimation procedure could then operate based on stored signal data. Since the estimation was conducted in this way, letting the procedure operate on signal data from real processes was a simple task.

During the initial phase of the project we did our very best to produce erroneous detections. We changed controller parameters, introduced time delays, altered the setpoint at the most inconvenient times and switched process models, everything in order to obtain false detections. When successful, we observed why the detection was faulty and how it could be avoided in the future. These findings resulted in the extended safety net described thoroughly in section 5.1, which is our main contribution to the procedure that Tore Hägglund presents in [4].

### 3.4 Implementation in ABB Control Builder

The ABB 800xA control system is a modern, state of the art, system for process control and automation. The system consists of industrial hardware and a module based software library. When designing control loops for the 800xA system, the tool ABB Control Builder is used. This application is described more extensively in chapter 6.

As opposed to Simulink, ABB 800xA is a true real time system. Every second that is simulated takes a second to simulate. Even if a process model is used instead of a real process, the simulations done using Control Builder's Test Mode-function are in a sense more realistic than the ones in Simulink. This is largely because interaction can be made, for example by changing set point at any time. When troubleshooting, the Online Editor, which lets the developer see all variables in the code change in real time, is a very powerful tool.

# 4. Processes and controllers

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*This chapter describes the different types of processes used in this master thesis and several methods for finding parameters to PID-controllers. Tuning procedures, both classic and modern, are described and tested.*

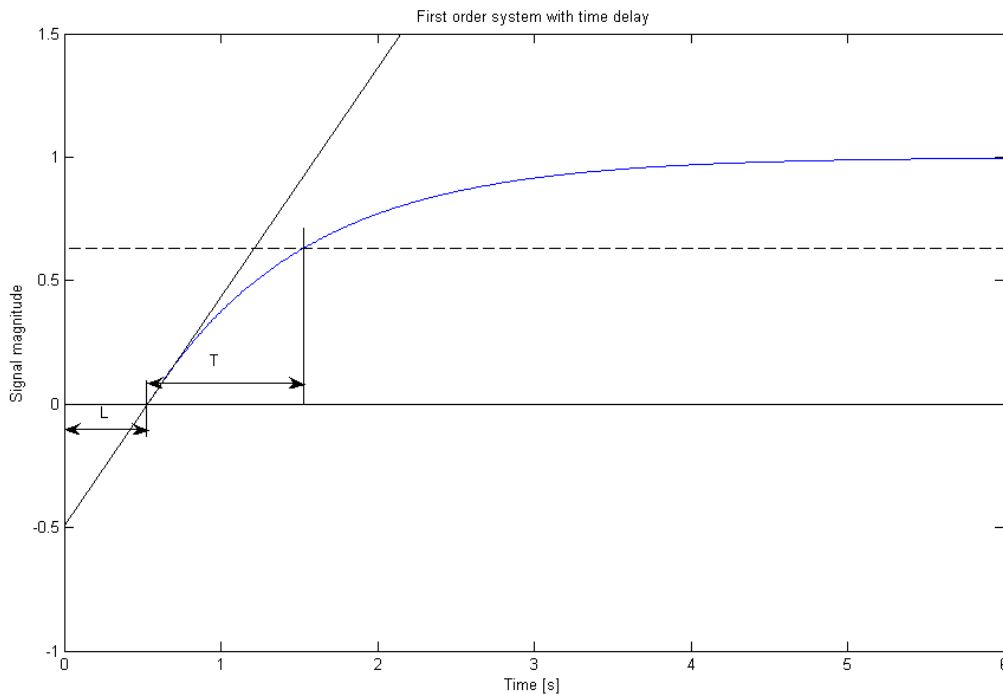
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## 4.1 The Test Batch

The processes used in this thesis are all suitable for PID control in the sense that they all have essentially monotone step responses. One way to characterize such processes is to study their dynamics, which can be obtained by fitting the process to a FOTD-model (First-Order system with Time Delay). A FOTD system can be seen as a three-parameter model, where  $K_p$  is the static process gain,  $L$  the time delay and  $T$  the time constant, also called lag.

$$P(s) = \frac{K_p}{1 + sT} e^{-sL}$$

The parameters  $L$  and  $T$  can both be obtained by observing the process step response. The response time  $T$  for stable systems can be measured as the time when the step response has reached 63% of its steady state value, see figure 4.1. The intersection between a tangent, drawn at the point where the slope of the response has its maximum, and the time axis gives the constant  $L$ .



**Figure 4.1** – Process step response for obtaining the time delay  $L$  and the time constant  $T$ . A step with amplitude 1 is fed to the process input at  $t=0$  s.

The test batch used in this thesis includes lag-dominated, delay-dominated, balanced and integrating processes. A lag-dominated process has a much larger process time constant  $\mathbb{T}$  than process delay  $\mathbb{L}$  and consequently for a delay dominated,  $\mathbb{L}$  is larger than  $\mathbb{T}$ . Some of the processes are not typical for industrial process control, but still include dynamics that can be of interest for the thesis. The first process in the test batch  $P_1$  is an integrating process with a minor time delay,

$$P_1(s) = \frac{1}{s(1 + 0.8s)} e^{-0.2s}.$$

The negative inverse of the describing function of backlash and the loop transfer function of the integrating process, controlled with a PID controller, are shown in figure 1.5. Because the two curves intersect, there is a possibility that a limit cycle will arise. This illustrates the control problem that can occur when backlash is introduced in the control loop. The transfer function for process  $P_2$  is balanced in the sense that neither lag nor delay is dominating the dynamics,

$$P_2(s) = \frac{1}{(1 + s)^4}.$$

The controller parameters used when controlling this process, and most other processes in the test batch, are obtained from the MIGO tuning rules explained more explicitly in section 4.2.  $P_3$  is a process with two oscillatory poles with relative damping  $\zeta=1/3$  and a third real pole in -1,

$$P_3(s) = \frac{9}{(s + 1)(s^2 + 2s + 9)}.$$

The process is not typical for industrial process control, but is still suitable for PID control. Systems with significant time delay, such as  $P_4$ , are very difficult to control,

$$P_4(s) = \frac{1}{2s + 1} e^{-4s}.$$

A general agreement seems to be that derivative action does not help much, thus a more sophisticated control than PID is recommended [3]. The two systems  $P_5$  and  $P_6$  are both third-order processes, but with a zero in  $P_6$ . Process  $P_7$  is a similar system, with eight poles in -1,

$$P_5(s) = \frac{1}{(1 + s)^3},$$

$$P_6(s) = \frac{1 - 0.5s}{(1 + s)^3},$$

$$P_7(s) = \frac{1}{(1 + s)^8}.$$

Small differences between PI and PID control can be expected in process  $P_8$  because of the delay-dominated dynamics and the fact that  $\mathbb{T}_d$  is, in most tuning methods, directly related to the time delay  $\mathbb{L}$ ,

$$P_8(s) = \frac{1}{(1 + 0.05s)^2} e^{-s}.$$



different behaviors are shown more explicitly in section 8.1.

## 4.2 Tuning Rules for PID Control

The controller used in this master thesis is a PI-/PID-controller on the form

$$u(t) = K \left( -y_f(t) + \frac{1}{T_i} \int (y_{sp}(t) - y_f(t)) dt - T_d \frac{dy_f(t)}{dt} \right). \quad (4.1)$$

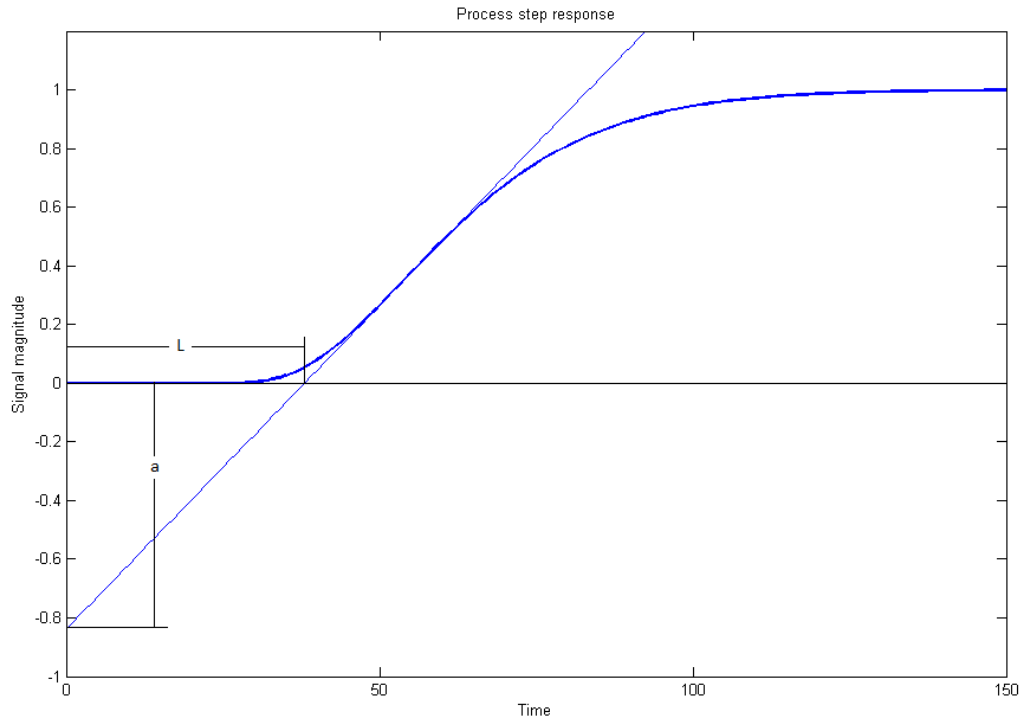
By choosing a decent tuning method and consequently well-tuned controller parameters, a much more accurate dead band can be estimated. The design of PID-controllers can be made in several different ways and is of great importance for the estimation procedure. The fact that simple tuning methods are being used, by persons with limited knowledge of control theory, when a much more advanced method could have been used instead, can result in poor estimations.

The estimation procedure used in this thesis requires a controller with integral action of some kind, i.e. PI or PID. Analyses of the tuning methods give insight into how the estimation procedure manages to handle different PI-/PID-controllers.

### 4.2.1 Ziegler-Nichols

Finding a reasonable set of control parameters does not require a complex analysis of the control problem. In 1942, Ziegler and Nichols presented two to be classical methods for determining the parameters of PID-controllers. The procedures are still widely used, much because of their simplicity. The parameters obtained are approximate and for better performance a more advanced method is required. The two different methods, the step response method and the frequency response method, both lead to rather aggressive control but still performs reasonably well for their simplicity.

The step response method is, as the name refers, designed based on a process step response. A tangent is drawn at the point where the slope of the step response has its maximum, see figure 4.2.



**Figure 4.2** – Process step response for obtaining the parameters  $a$  and  $L$  in the Ziegler-Nichols step response method.

The intersections between the tangent and the axis provide the constants  $a$  and  $L$ , used for determining the parameters [5].

The parameters for the frequency response method are obtained by connecting a proportional controller to the process and then slowly increasing the gain until the process starts to oscillate. The amplitude and the period of the oscillation match the point where the Nyquist diagram of the process transfer function intersects the negative real axis. With the so called ultimate gain  $K_u$  and the period  $T_u$  the parameters can be determined [5].

### 4.2.2 Lambda tuning

Lambda tuning is commonly used in process industry and can be seen as a special case of pole placement. By fitting a FOTD model to the process the controller parameters can be obtained. Provided that the parameters are chosen properly, lambda tuning can give relatively good results. This is a simple method that can result in a well-tuned controller in certain circumstances; various fixes can be made and consequently lead to a more accurate controller, but this requires insight on the process. The lambda tuning method is used when a restrained step response is desired, free from overshoots and decaying oscillations.

### 4.2.3 MIGO

The controller parameters to most of the processes in the test batch are obtained by the MIGO (M constrained Integral Gain Optimization) tuning rules. The MIGO design method is an advanced tuning procedure for obtaining accurate controllers. The method is designed to guarantee that the maximum value of the sensitivity function is less than a constant  $M$ . The robustness of a system is directly related to the maximum value of the sensitivity function, and so the MIGO tuning method can secure robustness with only the parameter  $M$  [5]. This is an advantage and results in an accurate controller, since the time delay  $L$  and the time constant  $T$  never have to be approximated. However, the circle criteria analysis requires a process model, which is a drawback for the algorithm.

A simplified version of the MIGO tuning rules is the AMIGO (Approximate MIGO) design method, which results in almost as well-tuned controllers as the original method. AMIGO is still a relatively advanced method, but is based on the time constant  $T$ , the time delay  $L$  and the static process gain  $K_p$ . Throughout this master thesis we have used the software designPID, which calculates controller parameters for a given process with known transfer function [8].

# 5. The safety net

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*The original safety conditions in [4] are, as it will be shown, insufficient for the backlash estimation procedure to be automatic and unsupervised. To guarantee the robustness of the procedure all deviations from the expected are tested, and consequently avoided by extending the safety net.*

---

## 5.1 The need for a safety net

In chapter 2 it was determined that one of the main objectives of this master thesis is to extend the safety net to guarantee the robustness of the backlash estimation procedure. The purpose of the safety net is to make sure that backlash estimates are only calculated when the system behavior resembles backlash. If this is done right, the estimations should be of limited variance, with a mean value close the true backlash. If, on the other hand, the safety net is insufficient, the estimates will most likely deviate significantly from the true backlash.

The estimation procedure described in [4] requires two conditions to be fulfilled for a backlash estimate to be calculated,  $\Delta t > 5T_i$  and  $\epsilon_{\max} < 2\Delta y$ . The first of the two conditions checks whether or not enough time has passed between the zero crossings, and is designed to verify that the signals are changing slowly enough for the assumption in equation (2.3) to hold. It also serves as a good way to avoid detecting noise as backlash, which would give rise to faulty detections. The second condition aims to make sure that only backlash-typical signal forms, like the one in figure 2.1 or 5.3, are detected.

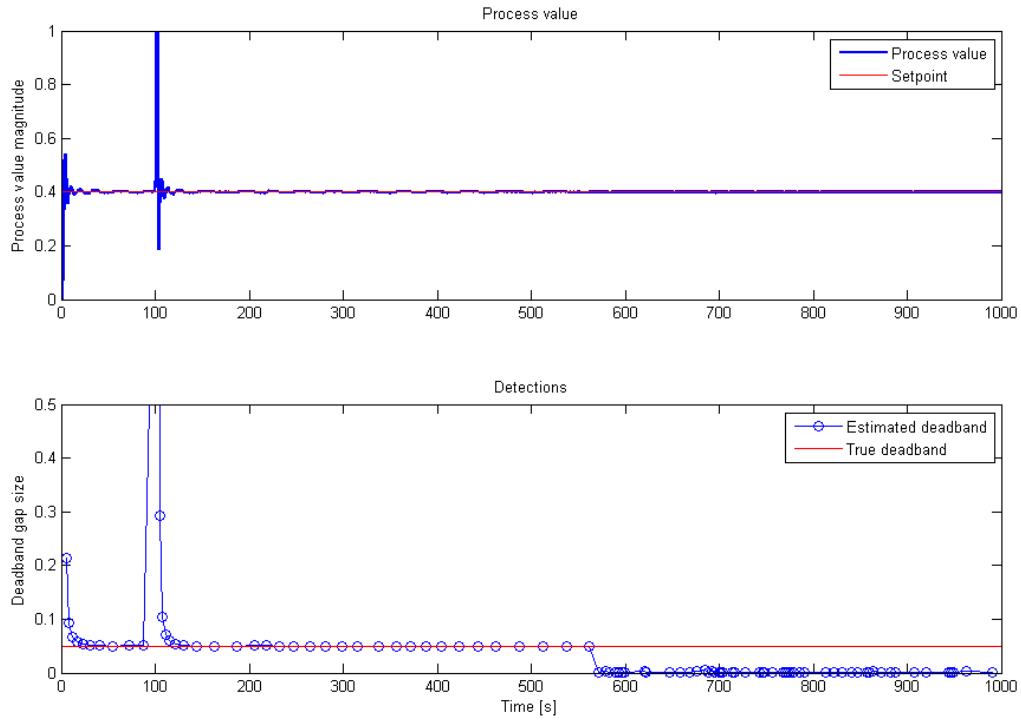
The original safety conditions are often sufficient, and would in most cases be enough to make good detections. However, the conditions are not sufficient for automatic, unsupervised detection designed only to present a value of the dead band gap. For such a procedure to be trustworthy, all deviations of the expected must be tested, avoided and/or compensated for.

## 5.2 Period time conditions

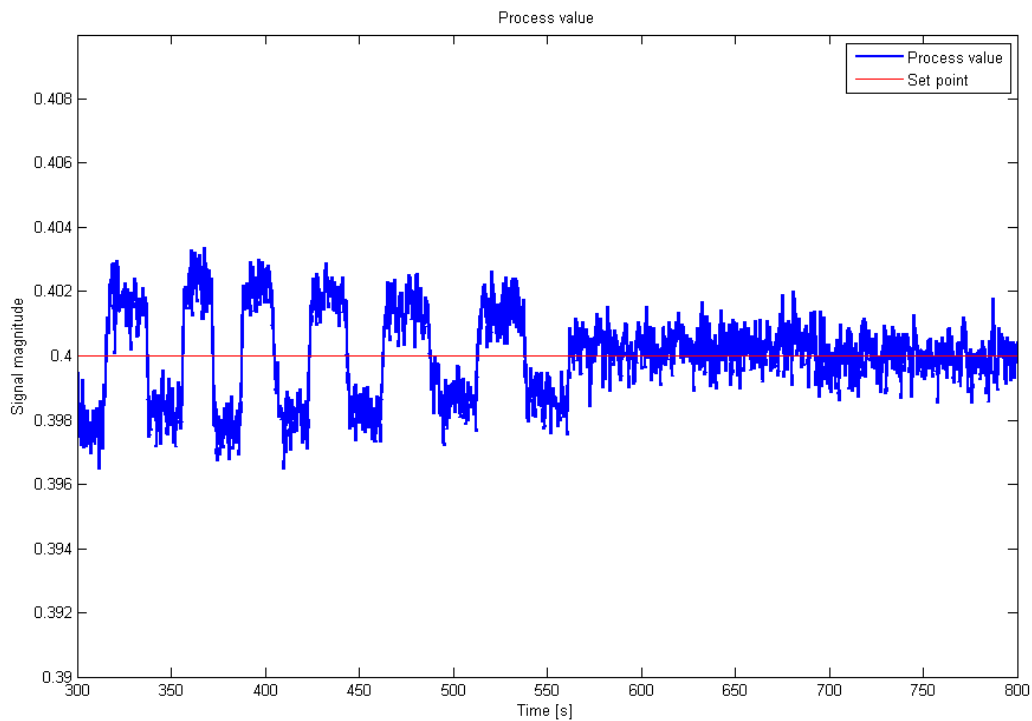
As discussed above, the original condition  $\Delta t > 5T_i$  is not sufficient for automatic detection. In particular, it was noted that when a process is controlled with a PI/PID-controller using a short integral time constant  $T_i$ , the time  $5T_i$  can be very short. For example, process  $P_3$  from the test batch,

$$P_3(s) = \frac{9}{(s+1)(s^2+2s+9)},$$

controlled with a MIGO-tuned PI-controller with controller parameters  $K=0.48$  and  $T_i=0.3117$ , only requires a zero-crossing period of 1.6 seconds. A simulation of process  $P_3$  is shown in figure 5.1, and a magnification of the same simulation between 300 and 800 seconds in figure 5.2. The simulation is 1000 seconds long, and consists of a step at  $t=0s$  and a load disturbance at  $t=100s$ .



**Figure 5.1** – Process value and detections vs. time. The detections around  $t=0$  s,  $t=100$  s and  $t > 550$  s are clearly unwanted, as they deviate from the true dead band value.

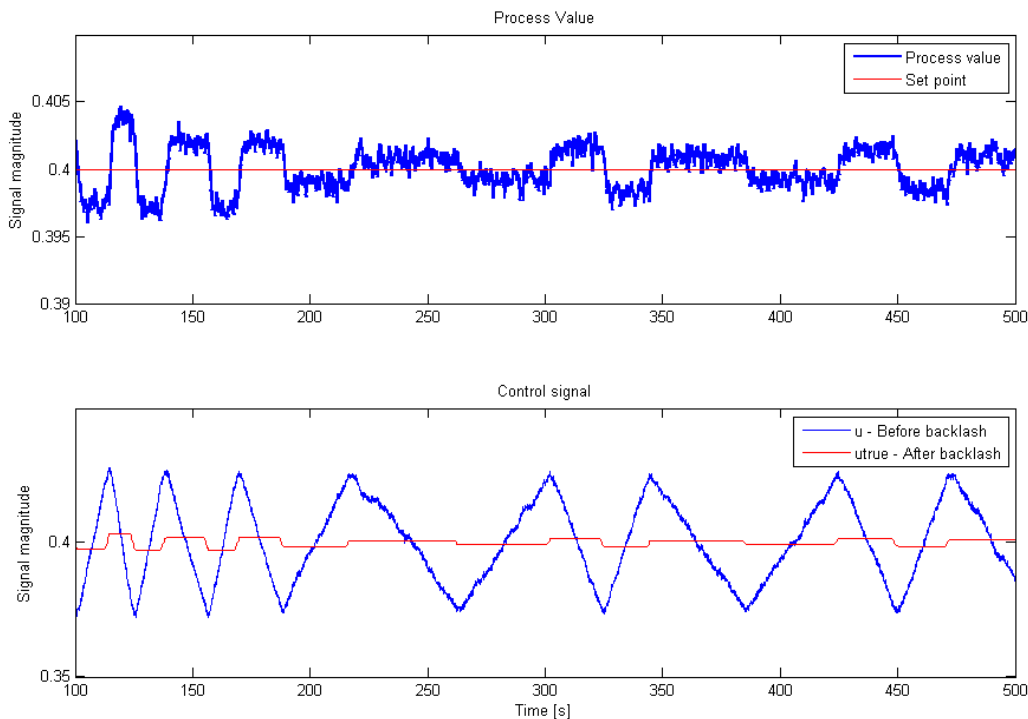


**Figure 5.2** – Magnification of the process value between  $t=300$  s and  $t=800$  s. Before  $t=550$  s, the process value shows typical backlash behavior. After  $t=550$  s, the zero crossings are without exception caused by noise instead of backlash behavior.

The zero-crossing period condition  $\Delta t > 5T_i$  only excludes detections with  $\Delta t < 1.6$  seconds, as  $T_i=0.3117$ . The noisy process value after  $t=550$  s crosses zero frequently, but sometimes the time between crossings is longer than  $5T_i$ , which leads to erroneous detections.

It is obvious that the detections made during the noisy time interval should not have been accepted. The easiest solution would be to increase the  $T_i$  coefficient or add an offset to the condition, resulting in, for example,  $\Delta t > 7T_i + 2$ , but this would reject valid detections from other processes and still have problems with even shorter integral time constants. A more complex condition, which takes the true dynamics of the process and the backlash non-linearity into consideration is needed.

When a stable process with backlash is controlled with a PI/PID-controller and the setpoint is constant the behavior in figure 5.3 is typical. The figure shows the process value  $y$ , the setpoint  $y_{sp}$  as well as the control signal before,  $u$ , and after,  $u_{true}$ , the backlash.



**Figure 5.3** – Typical backlash behavior in both process value and control signal. The control signal is clearly drifting back and forth, just enough to overcome the dead band before changing direction again.

As it should have been expected, the signals are strongly correlated. If the control signal from the controller  $u$  is approximated with a triangle wave, its period  $T_u$  would be  $2\Delta t$ , assuming  $\Delta t = \Delta t_1 = \Delta t_2 = \dots = \Delta t_n$ . In the simulation above the backlash dead band is  $0.05 = 5\%$ , a value that is also found to be, with good approximation, the amplitude of the triangle wave. This is not surprising, as the control signal drifts back and forth through the backlash, just enough to affect the true control signal a little before changing direction. In [4] it is stated that

$$\Delta u \approx \frac{K}{T_i} \Delta y \Delta t,$$

which can be used to calculate the derivative of the triangle wave

$$\left| \frac{\Delta u}{\Delta t} \right| \approx \frac{K}{T_i} \Delta y.$$

The same derivative can also be derived from the assumptions made from figure 5.3

$$\frac{\Delta u}{\Delta t} = \frac{d}{\Delta t},$$

where  $d$  is the dead band. Combining the two expressions for the derivative yields

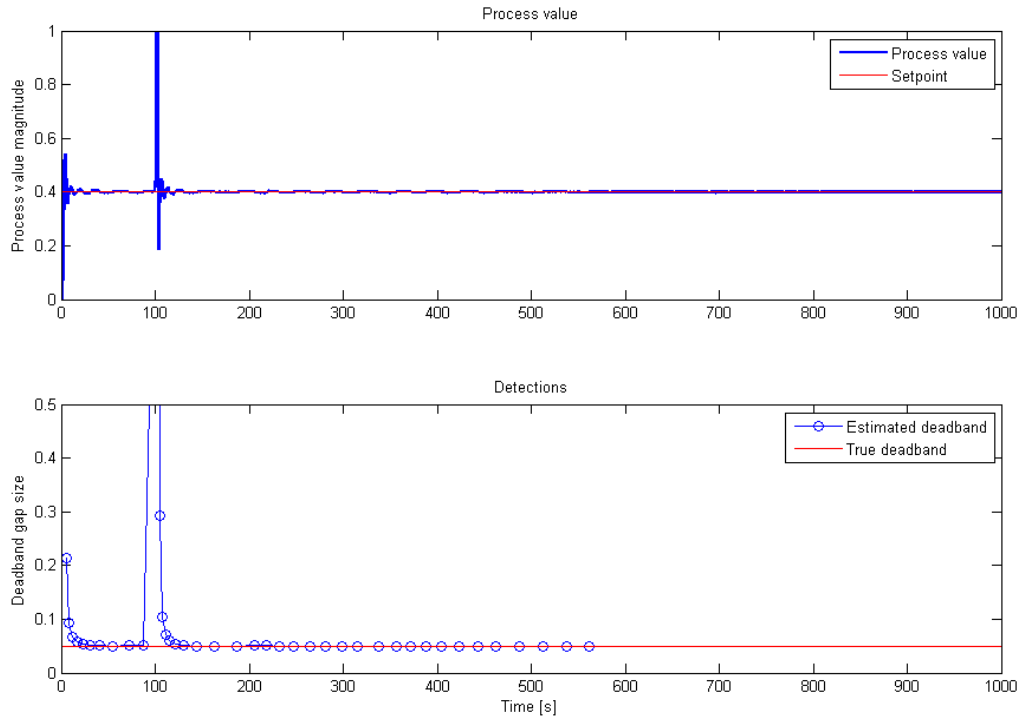
$$\Delta t = \frac{T_i d}{K \Delta y'}$$

This expression can be used as a condition for  $\Delta t$ , but includes the dead band, which is unknown. However, if the condition  $\Delta t > 5T_i$  is used initially, the new condition can be used as soon as some detections have been made. For the condition not to be too restrictive, it is suggested that half of the detected dead band is used in the expression. Thus,

$$\Delta t > \frac{T_i \hat{d}}{2K \Delta y'} \tag{5.1}$$

is a condition that guarantees that only valid backlash behavior is accepted in the first step of the safety net.

As  $\Delta y$  is in the denominator of equation (5.1), small deviations from setpoint must have a long zero-crossing period. Since noise is usually very small in magnitude and crosses zero frequently, it will be rejected by the condition. Figure 5.4 shows the same simulation as figure 5.1, but with the condition applied.



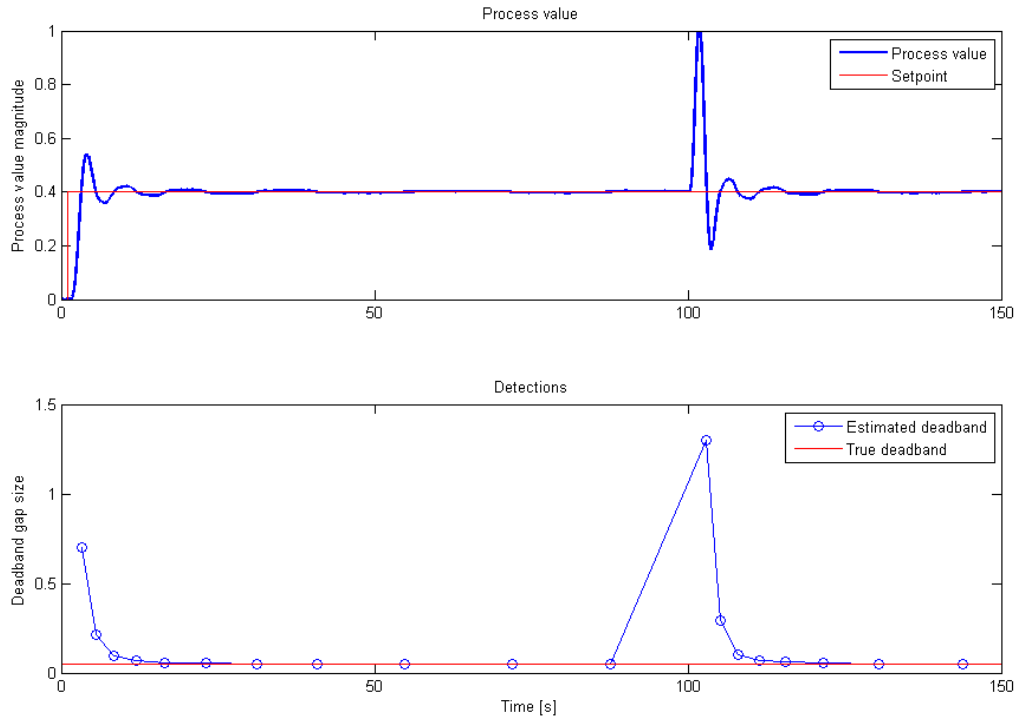
**Figure 5.4** – Detections with the time condition defined in equation (5.1) applied. All detections caused by the noisy process value at  $t > 550$  s are discarded. Compare with figure 5.1.

All the false detections with a dead band estimate close to zero are eliminated, and all the valid detections close to the true dead band 0.05 are left unchanged. This indicates that the condition from equation (5.1) is working as desired.

### 5.3 Curve form conditions

The period time conditions above guarantees that no detections will be made unless enough time passes between two consecutive zero crossings. However, it is not only backlash that can cause long zero crossing periods. For example, load disturbances and setpoint changes can lead to several long zero crossing periods before settling. If backlash estimation is performed on these periods, the estimates would be useless, why it is of importance to exclude such behavior. In figure 5.5, the first 150 seconds of the simulation in figure 5.1 are shown.





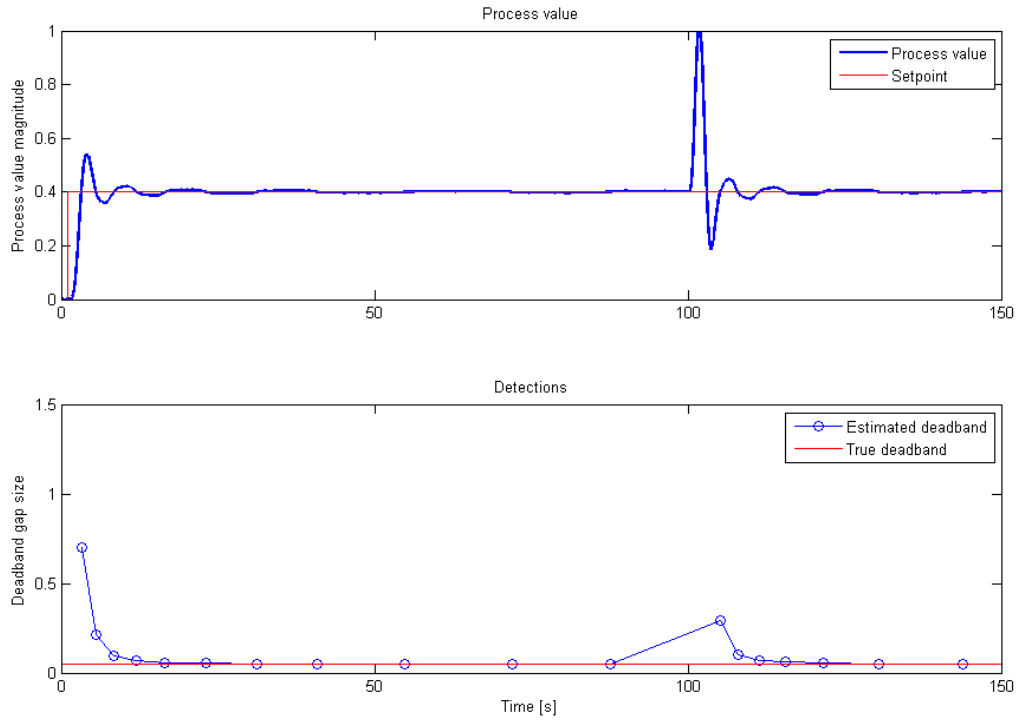
**Figure 5.5** – Detections during a 150 second long simulation starting with a step at  $t=1$  s and a load disturbance at  $t=100$  s. The detections directly after these two disturbances are clearly too high, even over 100% at  $t\approx 105$  s.

In [4], Tore Hägglund proposes a condition in order to exclude these deviating detections. If  $\epsilon_{\max}$  is the largest error throughout the previous zero crossing period and  $\Delta\bar{y}$  is the average error during the same period, detections are accepted if and only if:

$$\epsilon_{\max} < 2\Delta\bar{y} \quad (5.2)$$

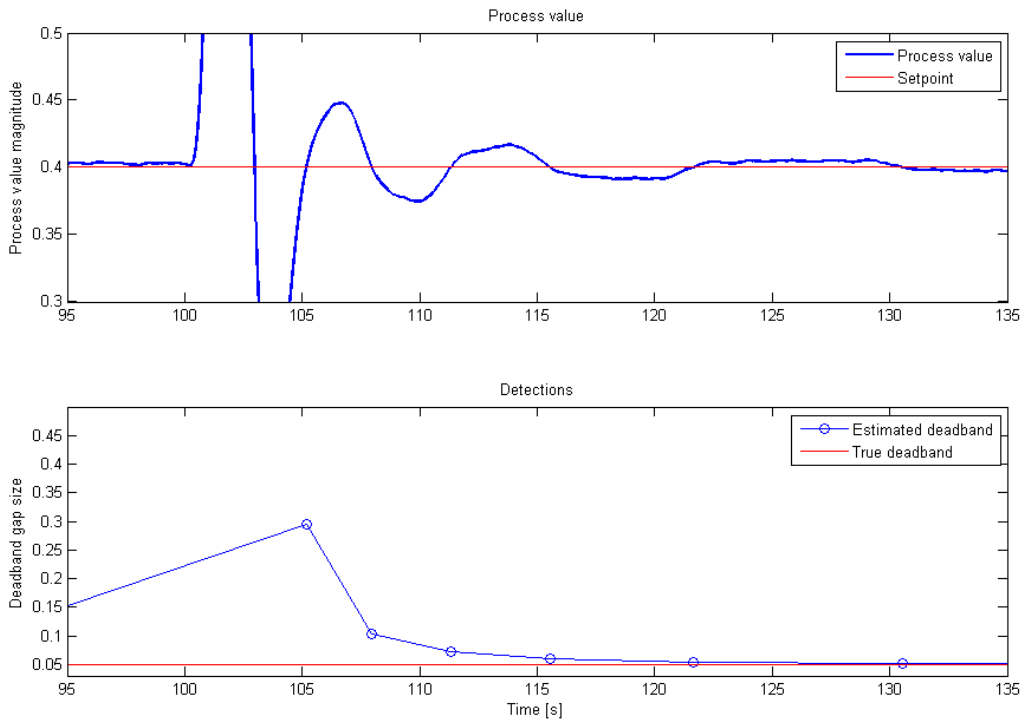
Requiring that the maximum error must not exceed two times the average error puts a condition on the shape of the error during the zero crossing period. For example, a perfect square wave has  $\epsilon_{\max} = \Delta\bar{y}$ , while for a triangle,  $\epsilon_{\max} = 2\Delta\bar{y}$ . When backlash is present, the typical process output is similar to a square wave, which without problem passes this condition. In reality, there is always an amount of noise added to the signal, which directly affects  $\epsilon_{\max}$ . The average amplitude  $\Delta\bar{y}$  on the other hand, is not affected by zero mean noise. This means that if the noise amplitude is very large, the condition (5.2) will make sure that no detection is made. Fast setpoint changes can also be detected with (5.2), as a change in  $y_{sp}$  directly changes  $\bar{y}$ . However, there are, or will be, other conditions for detecting setpoint changes (see section 5.3).

The same simulation as in figure 5.5 but with condition (5.2) applied can be studied in figure 5.6:



**Figure 5.6** – The condition  $\epsilon_{\max} < 2\Delta y$  excludes the most deviating detection, but the reference step and the load disturbance are still affecting the dead band estimates.

Figure 5.6 shows that although the condition  $\epsilon_{\max} < 2\Delta y$  excludes some detections, it does not exclude enough. The remaining deviating detections can all be connected to decaying oscillations in the process value. Figure 5.7 is a magnification of figure 5.6, which highlights the problem.

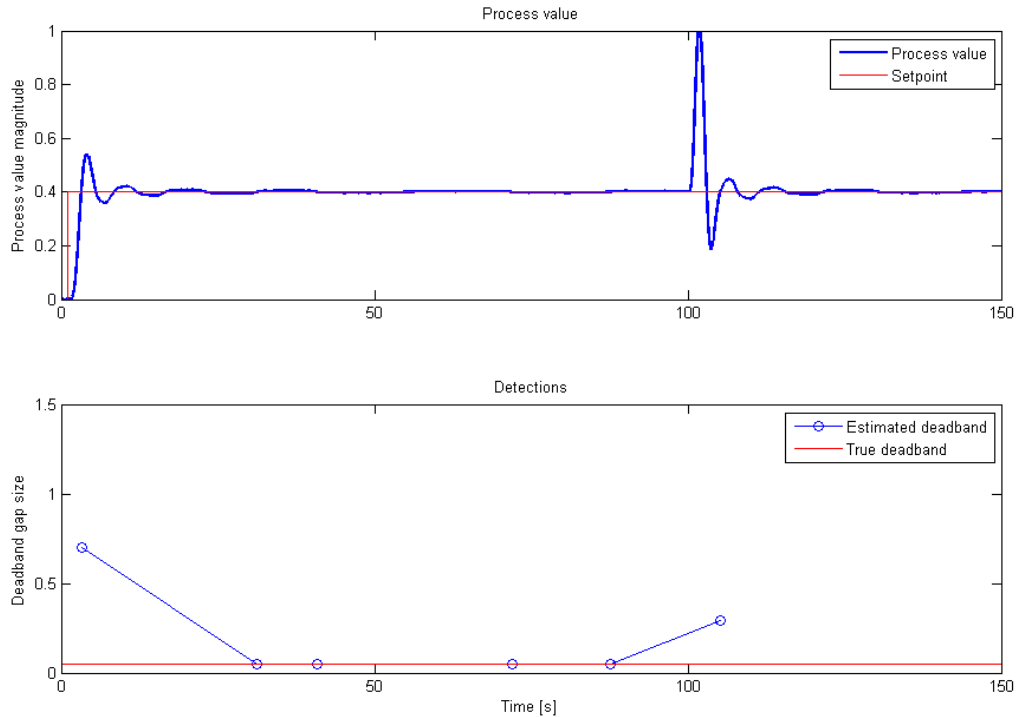


**Figure 5.7** – Magnification of the decaying oscillation caused by the load disturbance at  $t=100$  s. The zero crossings are not a result of the backlash, and should therefore be neglected by the backlash dead band estimation algorithm.

Oscillation caused by backlash, see for example figure 5.3, is usually constant in amplitude. The amplitude of a decaying oscillation is, as the name suggests, decaying. A simple way to detect this unwanted behavior would be to compare the amplitude of the current zero crossing period with the previous. If they are reasonably similar, it is likely caused by backlash. If the previous is larger than the current with a given factor, the detection is neglected as a result of a decaying oscillation. For example:

$$\left| \frac{\Delta y_{previous}}{\Delta y} \right| < 1.5, \quad (5.3)$$

would only be true if the amplitude has decreased less than 50%. Applying this condition to the simulation results in figure 5.8.

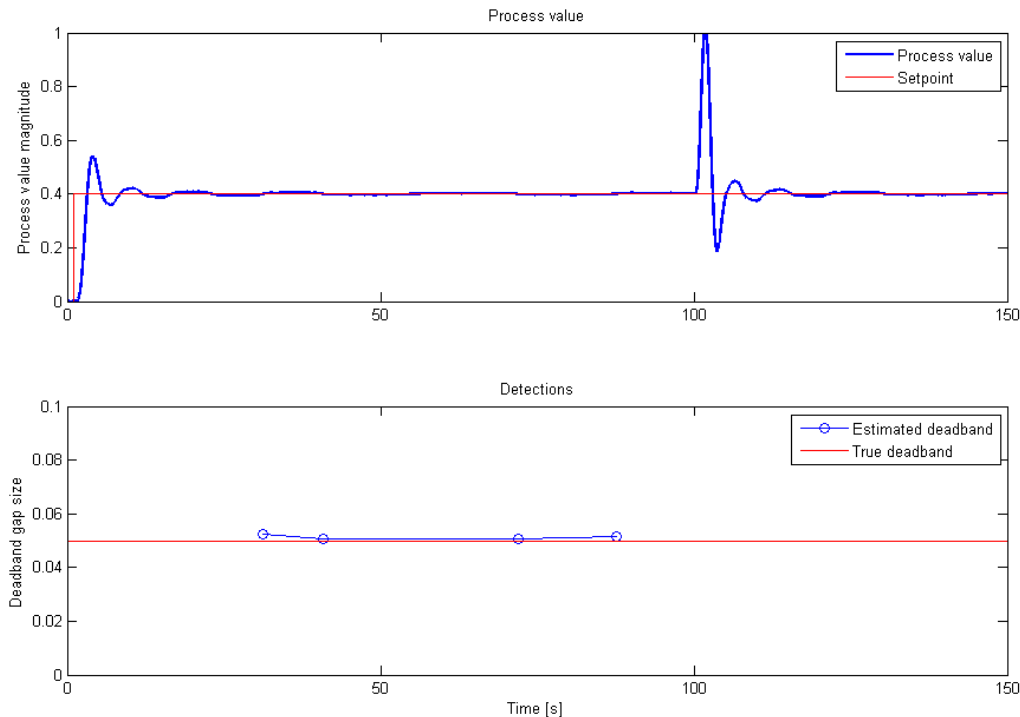


**Figure 5.8** – The condition for decaying amplitude removes most unwanted detections.

The two remaining deviating detections in figure 5.8 are not a result of decaying error amplitude, but of a sudden increase in error amplitude, caused by the setpoint step and the load disturbance, respectively. As it already has been stated, typical backlash behavior is constant in amplitude, which makes it possible to design a condition similar to (5.3), but for increasing amplitudes. In fact, equation (5.3) can be expanded with a lower limit, resulting in equation (5.4).

$$0.5 < \left| \frac{\Delta y_{previous}}{\Delta y} \right| < 1.5, \quad (5.4)$$

Applying condition (5.4) makes sure that no detection will be made if the error amplitude has been doubled, or more, since last zero crossing. Figure 5.9 shows the detections that are made with condition (5.4).



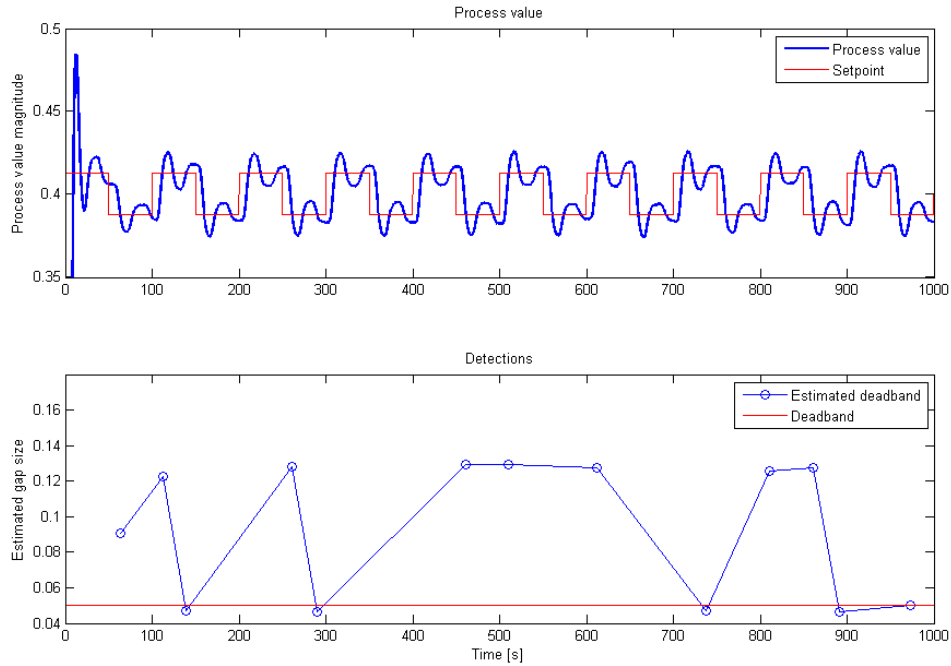
**Figure 5.9** – Remaining detections after condition (5.4) is applied. Note the change of scale.

Testing shows that condition (5.4) works well for all processes in the test batch, meaning that it does not affect correct detections significantly, yet it stops all erroneous detections caused by load disturbances. It should be noted, however, that even when no load disturbance is acting on the process, and no setpoint change is made, the error amplitude could indeed change more than what condition (5.4) permits. This can lead to the loss of some proper detection, but this price is low and must be paid.

It could be an advantage to let the operator set the lower and upper limits for condition (5.4), instead of using the constant limits 0.5 and 1.5, respectively. This is not done in the final implementation of this master thesis as it is reasoned that this would demand too much knowledge of the procedure from the operator, without really contributing to the quality of the estimation. As the backlash detection functionality is to be automatic, it must be kept as simple as possible.

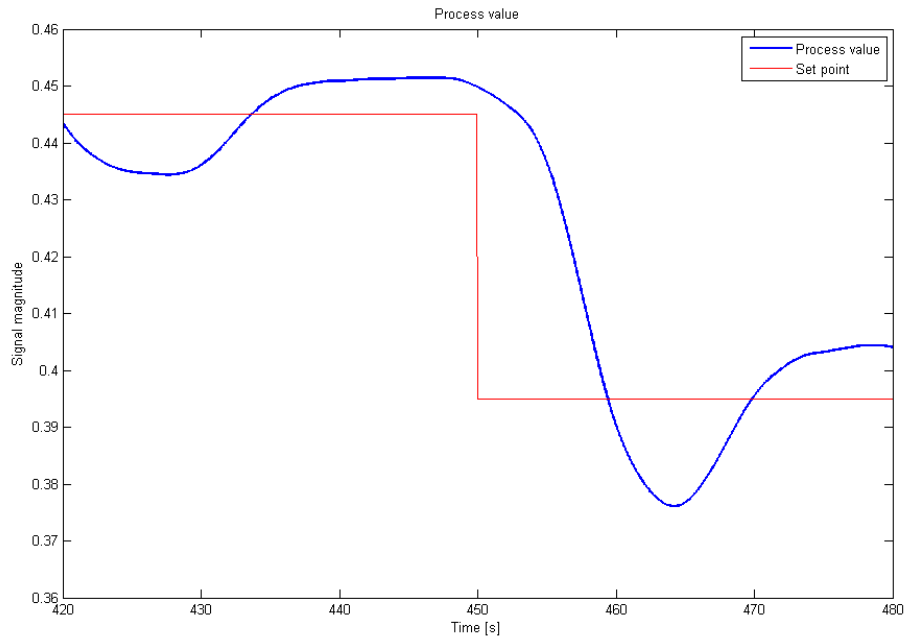
## 5.4 Setpoint condition

It is clear that the detections, both in manner of quality and quantity, depend a lot on the setpoint value. It is of great importance to have insight in varieties caused by the setpoint, why simulations with different setpoint forms have been done. A problem that can occur if the setpoint changes is well illustrated in figure 5.10.



**Figure 5.10** – Setpoint changes over time and give rise to faulty detections.

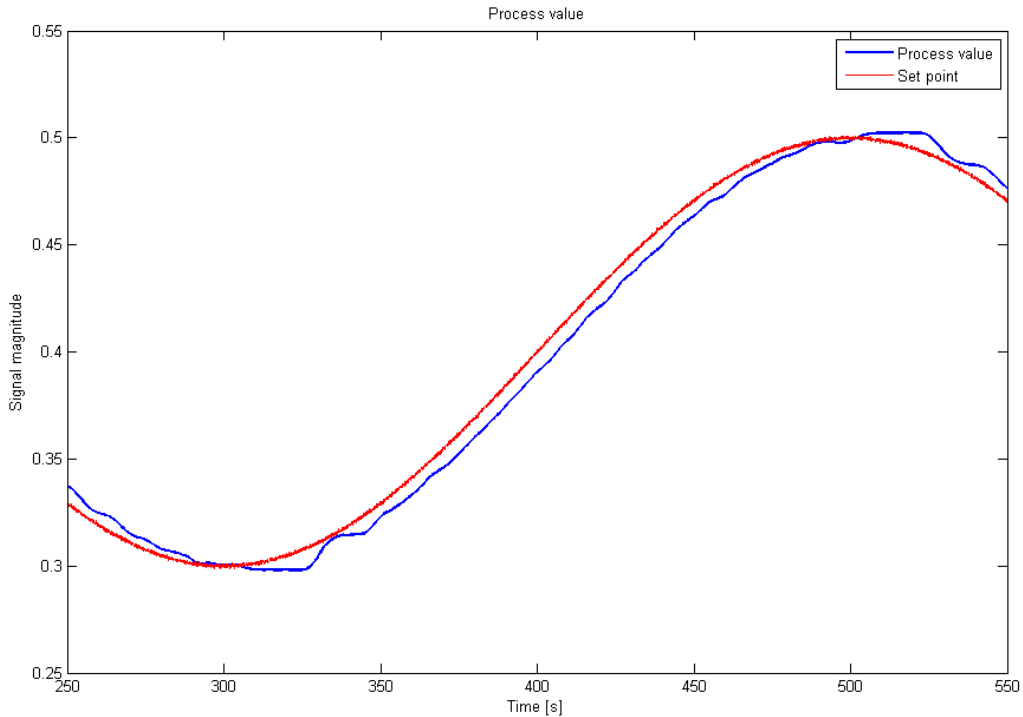
In the backlash estimation procedure, for calculating  $\Delta y$ , the control error is integrated between two zero crossings. In this case the change of setpoint causes significantly higher detections compared to the real dead band. A magnification of the zero crossing after 460 seconds is shown in figure 5.11, which shows that it is directly related to the change of setpoint. Since the safety net of the estimation procedure does not yet contain a condition for changes of the setpoint, the interval in the figure gives rise to an incorrect detection, as the integrated error is much larger than it would be without a change of setpoint.



**Figure 5.11** – Zero crossings caused by a change of setpoint. The integrated error is the area bounded by the set point and the process value.

In similar cases the detection will be eliminated by  $e_{\max} < 2\Delta y$ , but in this particular case the integral error is large which leads to a backlash estimation of 13%, when the real value is 5%.

Similar problems can occur if a process is controlled with a slow and restrained controller. Simulations with a noisy sine shaped setpoint were done, to replicate an external setpoint in an industrial environment. The frequency of the setpoint signal is high and the controller parameters restrained, which leads to a “chasing” process value, see figure 5.12.



**Figure 5.12** – Process value and setpoint. The process value does not cross the setpoint until it changes direction.

Since the backlash estimation procedure integrates the error between the zero crossings, the appearance in the figure is defined as backlash and provides poor estimations.

A solution to the problems, that also works on-line, is to compare the setpoint values between the zero crossings. If the difference between the crossings is large relative to  $\Delta y$ , the detection is false and should be eliminated. By eliminating detections the risk of estimating a false backlash is radically reduced, but a longer time period is needed for an accurate result. The boundary

$$\Delta y_{sp} < \Delta y \quad (5.5)$$

discovers large changes in setpoint and provides good results in both cases explained above. It is an advantage that the boundary is simple and strict since the estimation procedure is to be automatic.



## 6. Implementation in ABB Control Builder

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*The backlash estimation procedure is implemented in ABB Control Builder as a control module in a prototype library. Standard MatLab Simulink components, such as backlash and noise, are created for simulations in Control Builder to work.*

---

### 6.1 Control Builder

The implementation part of the master thesis is made with ABB Control Builder Compact and will result in a prototype library with the detection method as a control module. Control Builder is a software used for PLC programming in an ABB 800xA environment. All the programming languages in the international standard IEC 61131-3 can be used, such as Structured Text (ST), Ladder Diagram (LD), Sequential Function Chart (SFC), Instruction List (IL) and Function Block Diagram (FBD) [6]. MatLab Simulink, used for simulations, and Control Builder are much alike, but there are some central differences and several standard components missing in the latter. Therefore, for the model to work, a couple of components had to be created, all programmed in structured text.

Control Builder uses blocks, so called control modules, for constructing simulation models. The modules are connected to each other through nodes, also called *Control Connections*. The nodes can send and receive information both forward and backward in the loop. The directional property of the control connection is crucial in a real time environment, as it makes it possible to execute a control loop in sequential order, each sample period. If every single component in the control loop would calculate its output based on the input from last sample, the total time delay of the loop would be far too long.

Not only the input and output to and from the control modules are shared over the control connections. In addition, status signals are sent, indicating if some error has occurred in the loop. This way, control modules can for example receive information about when a maximum or minimum value has been reached.

For interacting with simulations in real time, every control module is connected to an interaction window that allows the user to edit parameters, change modes, activate optional functionality etc.

### 6.2 NoiseCC

For simulating noise in Control Builder a control module is created, called NoiseCC. A random generator is used that provides a rectangular distributed range of random numbers between zero and one. The implementation is done in structured text, see code block 6.1. The control module can be connected anywhere in the control loop and requires only the amplitude of the noise.

<b>NoiseCC</b> - <i>Control Module</i>
--

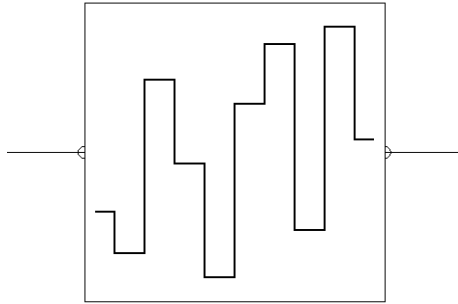
```

Noise := (RandomRect(RandomGenerator) - 0.5) * 2;
Out.Forward.Value := In.Forward.Value + Power*Noise;

```

**Code block 6.1** – Implementation of NoiseCC in Control Builder.

The variable `Power` is set by the user in the interaction window and corresponds to the size of the noise amplitude. The control module, as it appears in Control Builder, can be seen in figure 6.1.



**Figure 6.1** – Control module NoiseCC.

The noise is added to the input of the control module, and the sum is fed to the output.

## 6.3 BackLashCC

The control module BackLashCC is created for representing a backlash in a Control Builder environment. The module is easily implemented with an if-block programmed in structured text, see code block 6.2. The variable `deadband` is given by the user in the interaction window and corresponds to the size of the dead band.

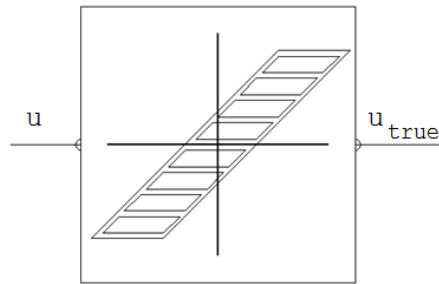
```

BackLashCC - Control Module
if input > outputOld + deadband/2 then
    output := input - deadband/2;
elseif input < outputOld - deadband/2 then
    output := input + deadband/2;
else
    output := outputOld;
end_if;
outputOld := output;

```

**Code block 6.2** – Implementation of BackLashCC in Control Builder.

The module is implemented with the code above and is connected between the controller and the process, with input `u` and output `utrue`.

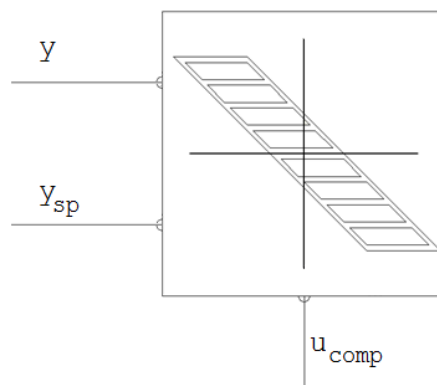


**Figure 6.2** – Control module *BackLashCC*.

Figure 6.2 shows the control module *BackLashCC*, as it appears in Control Builder.

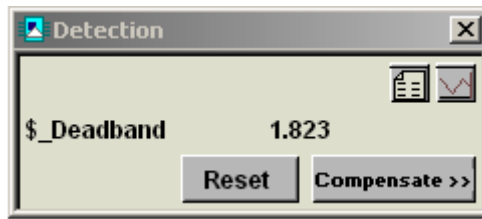
## 6.4 *BackLashDetectionCC*

*BackLashDetectionCC* is the main result of the master thesis and contains backlash detection, estimation and compensation functions. With the reference signal and the process value as inputs and the controller parameters known, a backlash can be detected and estimated as in equation (2.4). As discussed in section 2.2, a compensation output signal is also created and may be connected to the feed forward input on the controller. The stand-alone control module *BackLashDetectionCC* can be seen in figure 6.3.



**Figure 6.3** – Stand-alone control module *BackLashDetectionCC*.

The interaction window for the control module allows the user to control the backlash detection procedure. The current dead band estimate is seen in the main interaction window together with several operation buttons, see figure 6.4. The user can choose to view a graph with detections made in time from the graph button and the input parameters to the control module can be changed in the parameter interaction window. Finally the user has the possibility to compensate for the backlash by pressing the compensate button, were the detections made after compensation are also viewed.

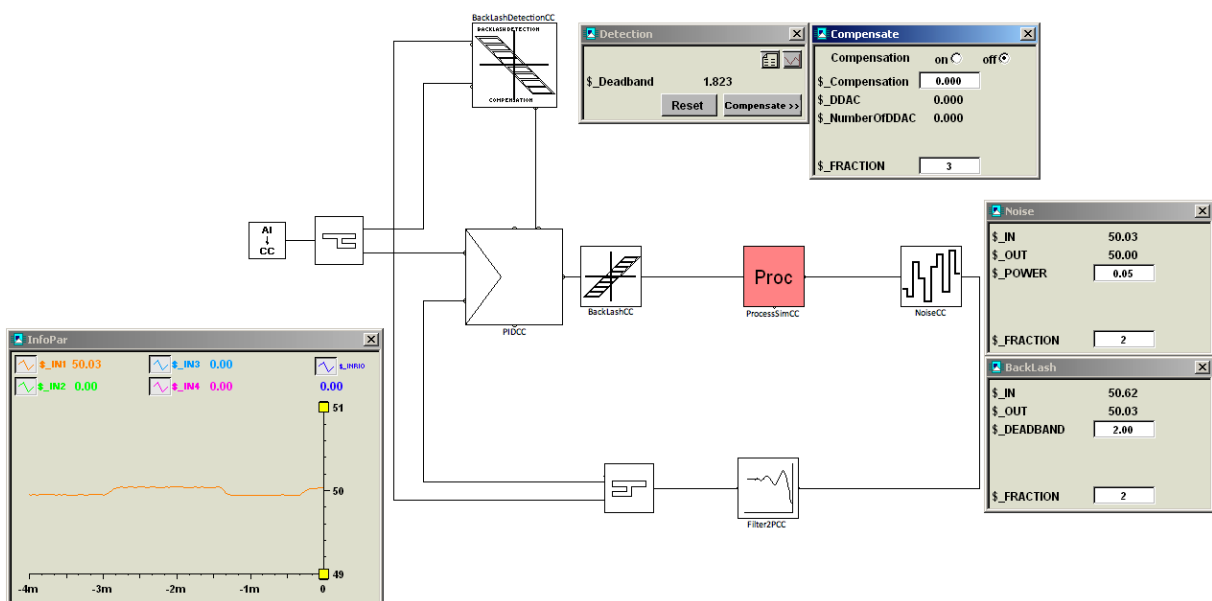


**Figure 6.4** – Interaction window for BackLashDetectionCC with the current dead band estimate shown.

BackLashDetectionCC is currently implemented as a stand-alone control module with the controller parameters received from the parameter interaction window. The control module could, in the future, be implemented as a part of the standard Control Builder component PidAdvancedCC. The module PidAdvancedCC is a controller used when more advanced functions than the ones represented in PidCC are required.

## 6.5 Control Builder system

A complete system is implemented, for simulations in Control Builder to work, and includes the same complexity and functionality as in MatLab Simulink. The control modules are connected as in figure 6.5. Except for the control modules NoiseCC, BackLashCC and BackLashDetectionCC above, a couple of standard components are being used. PidCC is a standard controller in Control Builder and includes the controller parameters and basic control functions, such as the AutoTuner. ProcessSimCC is a prototype module in the software and consists of two sections of low-pass filters with time delay. The control module is used for simulating different types of processes in the test batch. The last module Filter2PCC is another standard component in Control Builder and is, as the name indicates, filtering the signal.



**Figure 6.5** – Model constructed with Control Builder for simulating backlash in a control loop.

The figure shows how the process value changes over time, in the interaction window called InfoPar, with backlash in the control loop. The dead band is set to 2.0% and the filtered detections when compensation is inactive are 1.8%, which is considered to be a good result.

## 6.6 Final implementation

As mentioned above, the functions in ABB Control Builder are implemented as separate modules that can be connected using Control Connections. When new functionality is to be added, it must be decided whether to add an additional module or expand an existing one. Some functions are obvious; the BackLashCC module defined in section 6.3 should without doubt be implemented as a new control module, while the AutoTuner-functionality was rightfully added to the PidCC module instead of being implemented as a stand-alone module. Other functionality implementations are less obvious.

The BackLashDetectionCC module has this far been referenced to as a stand-alone component. The upside of this is that backlash detection is only added to a system when necessary. It also helps to keep different functions clearly separated and therefore as simple as possible. The downside of a detached implementation is that less information is available. If BackLashDetectionCC is implemented as in figure 6.5, the controller parameters must be set manually. If the controller parameters would change, for example after an AutoTuning has been performed, they have to be manually changed in BackLashDetectionCC. It can also be seen in figure 6.5 that two branches and three Control Connections must be added to connect the BackLashDetectionCC. The input connections are identical with those entering PidCC, hence the branches. It is clear that BackLashDetectionCC could very well be implemented inside a PID-controller.

As it could not be decided within the time frame of this project how the final implementation should be done, both possible alternatives are considered throughout the rest of this master thesis. It should be mentioned that the BackLashDetectionCC as it is described here could easily be connected inside a PID-control module such as PidCC, or more likely PidAdvancedCC.

# 7. Investigation and analysis

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*During the completion of this master thesis, several unanswered questions appeared. Many of these questions had an intuitive answer, but had not been proved. Such proofs and verifications are collected in this chapter, together with some functionality that was added to the detection procedure during the final stages of the project.*

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## 7.1 Saturation of control signal

When controlling a process with a PI-/PID-controller, the control signal is calculated as:

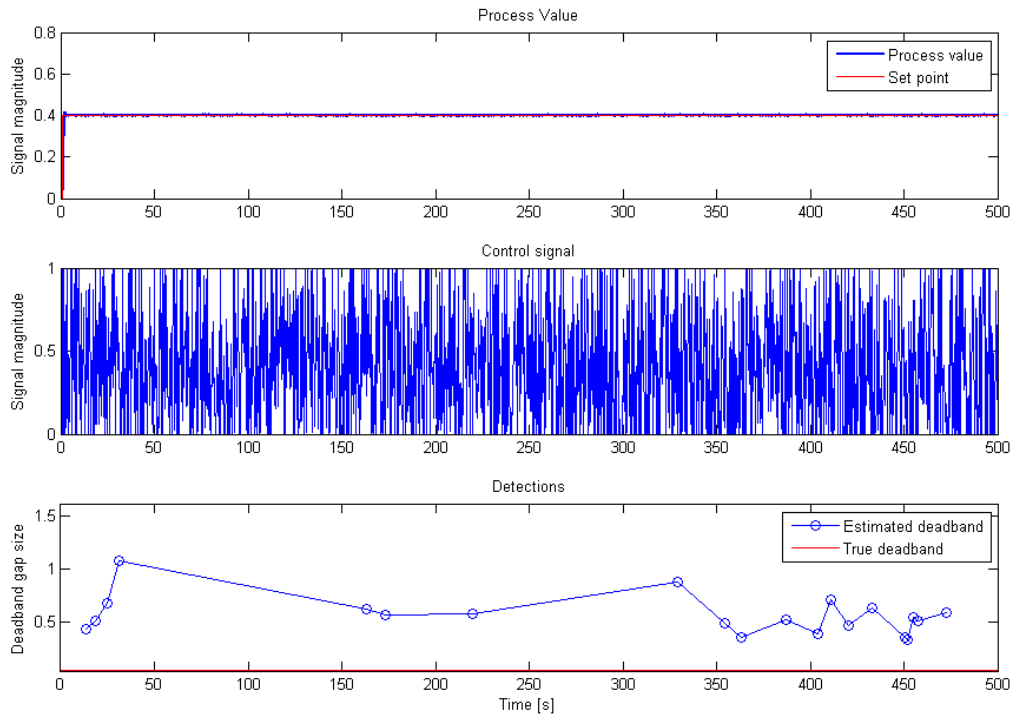
$$u = K \left( -y_{sp} + \frac{1}{T_i} \int_0^t (y_{sp} - y_f) dt - T_d \dot{y}_f(t) \right).$$

Even if the setpoint and process value are limited within a certain interval, which usually is the case, the control signal can be unlimited, due to the integral action. Even though the control signal in theory might be infinitely large, there are physical limits on the actuators and control hardware. In this case the ABB 800xA system works with signals in the range 4 to 20 mA. This means that in reality, the control signal is indeed limited, i.e. it may become *saturated*.

The backlash dead band estimation algorithm that is the topic of this paper is sensitive to saturation. As explained in section 2.1, the dead band is estimated based on how much control signal is needed in order to drift through the dead band. The change of control signal between two zero crossings,  $\Delta u$ , gives an approximate estimate of the dead band and can be written as:

$$\Delta u \approx \frac{K}{T_i} \Delta y \Delta t. \tag{7.1}$$

For this equation to hold, it is assumed that the control signal is not saturated. If saturation is present and is affecting the control signal, erroneous detections will be produced. In figure 7.1, a simulation with saturated control signal is shown.

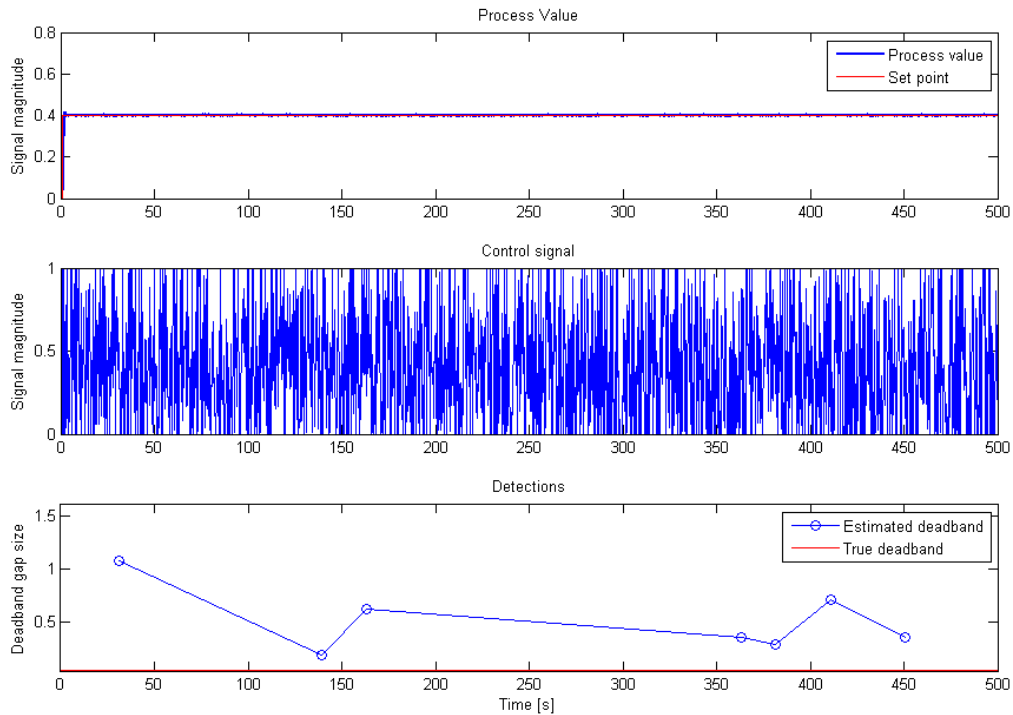


**Figure 7.1** – Erroneous detections caused by a strongly saturated control signal.

As it can be seen in figure 7.1, the dead band detections are more than ten times as large as the true dead band ( $0.05 = 5\%$ ). This is a direct effect of the saturation. Since the control signal is saturated, it will take longer time to drift through the dead band than it would if the control signal was unlimited in magnitude. The extra time it takes to cross the dead band directly effects the estimated dead band, as the estimation is proportional to the time  $\Delta t$ .

When saturation is present, action needs to be taken. The first step is to identify that the control signal has been limited by saturation to some extent during the last zero crossing interval. This can be done in several ways, depending on how the estimation procedure is to be implemented.

The most problematic situation is if the backlash detection is implemented as a stand-alone control module, with  $y$  and  $y_{sp}$  as only inputs. If this is the case, the only knowledge of the control signal is its relative change during the zero crossing period  $\Delta u$ , calculated according to equation (7.1). If this change is larger than the control signal span,  $u_{max} - u_{min}$ , then obviously the control signal has been more or less saturated. This requires information of the parameters  $u_{min}$  and  $u_{max}$ , but these are usually 0 and 100, respectively. In figure 7.2, this condition is used to filter out detections.



**Figure 7.2** – Detections with saturated control signal. Some detections are removed with the condition  $\Delta u < u_{max} - u_{min}$ . Compare with figure 7.1.

As it can be seen in figure 7.2, this condition is insufficient. If backlash detection is to be implemented as a feature of the PidAdvancedCC control module many doors open, as discussed in section 6.6. This includes direct access to the control signal, the  $u_{min}/u_{max}$ -variables and the saturation status of the controller. Thus, the question of whether or not the controller is saturated can be answered in two ways. The straight forward approach, to check if the control signal  $u$  has reached  $u_{max}$  or  $u_{min}$  during the zero crossing period, is perhaps the least advantageous. It would of course be very useful, and eliminate all detections from figure 7.1, but only saturation of the controller itself would be detected. It would not, for example, notice if a slave controller in a cascade loop saturated or if an actuator has reached its end position.

The second approach is to monitor the saturation status of the controller. Recall section 6.1, where the Control Connection tool in Control Builder is described. When some part of a control loop reaches its minimum or maximum value, the flag `MinReached` or `MaxReached` is sent backwards in the control loop. If a flag is received, or sent, by the controller, some saturation is present in the control loop, and the safest action to take for the estimation procedure is to neglect the following detection. By doing so it is made sure that no saturation of any part of the control loop affects the estimated backlash gap. As every control module has a responsibility to pass on the saturation-flags, it is sufficient to supervision the saturation status of the control connection connected to the feed forward input of controller. By implementing this, all backlash estimations in figure 7.2 would be eliminated.



## 7.2 The process parameter $K_p$

In a perfect plant, in a perfect world, every process model would be known by the operator. This is unfortunately not the case. In the real world, rather few process parameters are available. On the other hand, since most industrial processes are controlled with PI-/PID-controllers no exact process model is needed to obtain satisfactory closed loop behavior [7]. If a procedure like the one described in [4] is to be used, as little information about the process as possible should be required. In section 2.1 it is stated that the only information about the process that must be known is the static process gain,  $K_p$ . Even this parameter could be unknown to the operator, why it is of interest to investigate how much the algorithm is influenced by errors in the  $K_p$ -parameter.

### 7.2.1 The influence of $K_p$

The estimated dead band was derived in 2.4 as

$$\hat{d} = \frac{K\Delta y\Delta t}{T_i} - \frac{\Delta y}{K_p} = K\Delta y \left( \frac{\Delta t}{T_i} - \frac{1}{KK_p} \right). \quad (7.2)$$

This equation is clearly separated in two parts, one independent of  $K_p$  and one dependent of  $K_p$ . The safety net condition for zero-crossing period time guarantees that:

$$\Delta t > 5T_i, \quad (7.3)$$

and thus the  $K_p$ -independent part of the backlash estimate:

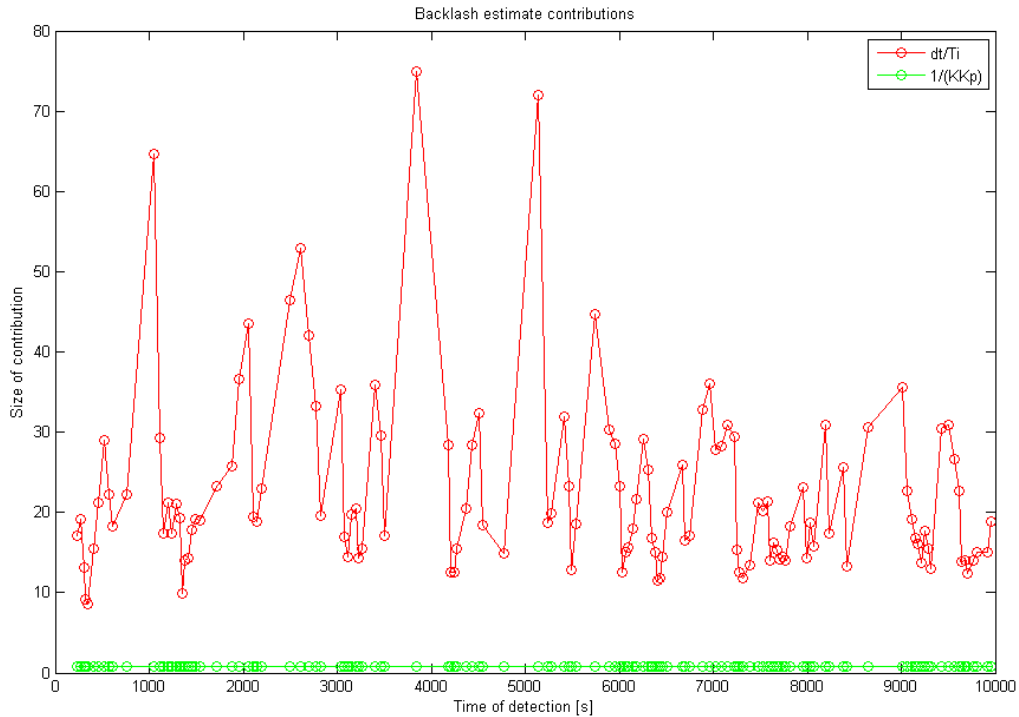
$$\frac{\Delta t}{T_i} > 5$$

If the controller is well tuned the product  $K_p K$  is limited [3]:

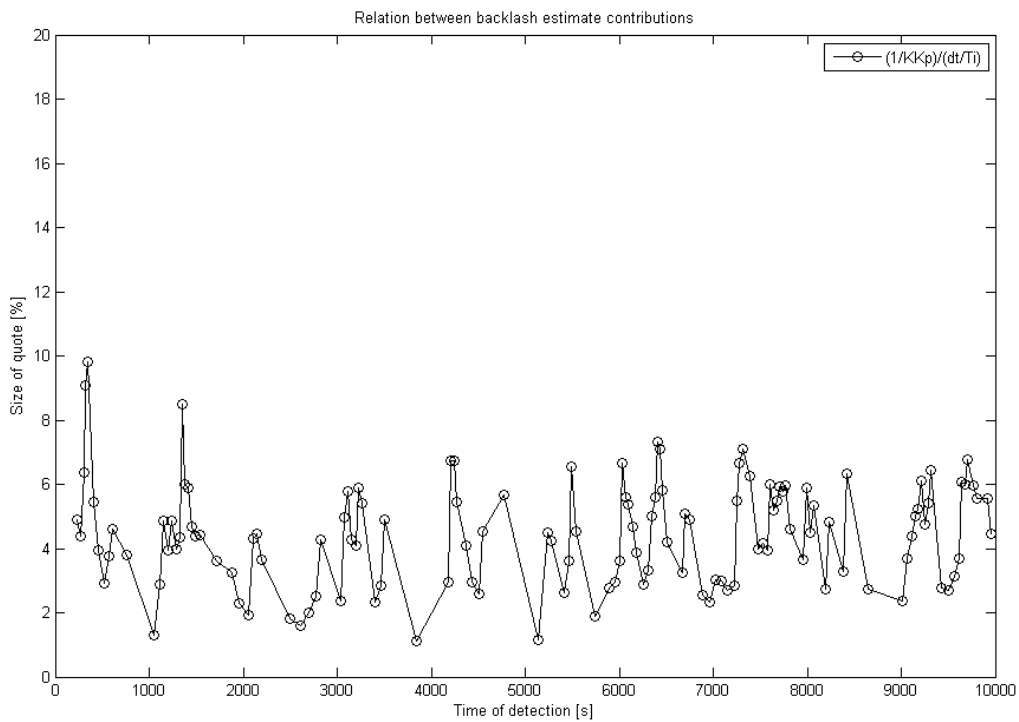
$$\begin{aligned} 0.5 < KK_p < 1, \\ 1 < \frac{1}{KK_p} < 2. \end{aligned} \quad (7.4)$$

Still, the contribution from the  $K_p$ -part can in the worst case be as large as 40% of the detection value. This shows that  $K_p$  is an important parameter that can cause large errors in detections if not correctly set.

In practice, the zero-crossing time period is in most cases much longer than  $5T_i$ . This suggests that the contribution from  $K_p$  is actually seldom as large as 40% of the detection value. Figure 7.3 and 7.4 indicates a typical influence of  $K_p$  during simulation, where  $K_p$  equals 1 and the controller gain is 1.2.



**Figure 7.3** – The  $K_p$ -independent part (red) of the backlash estimate is considerably larger than the  $K_p$ -dependent part (green). This suggests that the method is more insensitive to deviations in  $K_p$  than equations (7.2) – (7.4) implies.



**Figure 7.4** – The quotient between the  $K_p$ -dependent and  $K_p$ -independent part of the backlash estimate never exceeds 10% in this simulation, as opposed to the worst case 40% from theory.

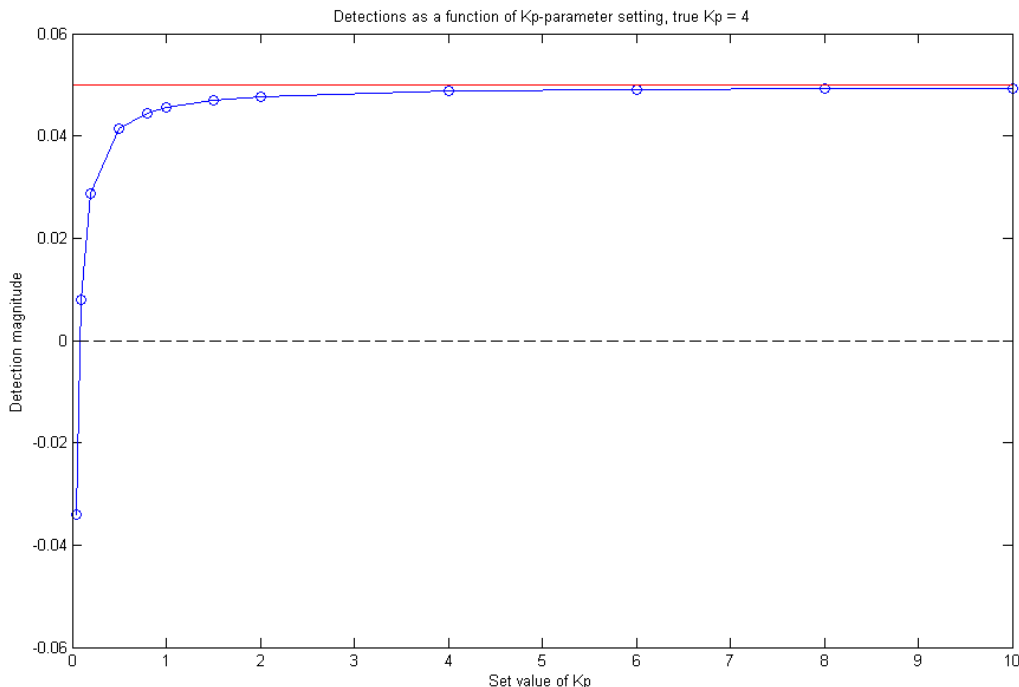
## 7.2.2 A default value of $K_p$

If the static gain is unknown a default value is needed in order for the algorithm to run. In [4], it is suggested to use a default value of 1.5, as most industrial processes use normalized signals with  $K_p \approx 1$ . This default value, it is stated, results in a detection error of less than 20%, under the assumption that the true process gain is between 1 and 3.4 [4].

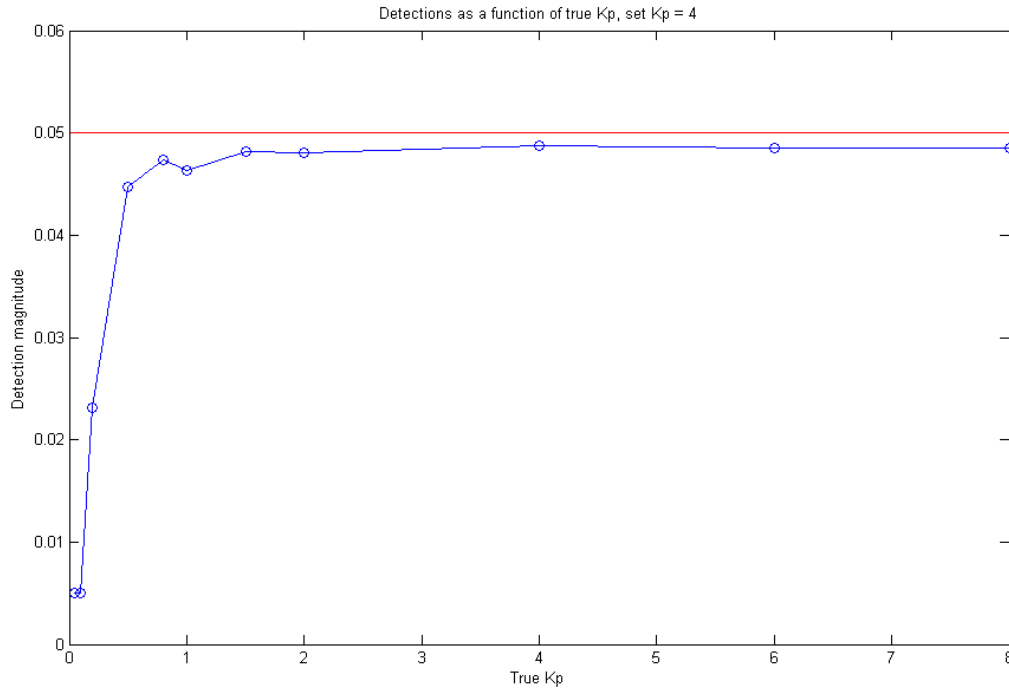
As discussed in 6.6, the backlash detection algorithm might very well be implemented in the PidAdvancedCC control module. PidAdvancedCC is a PID-controller with added functionality such as gain scheduling, setpoint ramping and *AutoTuner*. The *AutoTuner* is a function for automatic estimation of suitable PID-parameters [8]. The Autotuner algorithm calculates the static process gain, which it then uses to calculate suitable controller parameters. This value of  $K_p$  can be used in the backlash detection algorithm if autotuning has been performed.

## 7.2.3 Error in $K_p$

In the previous sections it has been shown both that  $K_p$  is an important parameter and, quite contradictory, that it is of little importance to the dead band estimate in simulation. What is truly interesting is on the other hand not the influence of the  $K_p$ -parameter, but the influence of *error in the  $K_p$ -parameter*. It is obvious that if  $K_p$  is set to a very low value, it will reduce the magnitude of the estimations significantly. In figure 7.5 and 7.6 detections from several simulations are shown. In figure 7.5 the true value of  $K_p$  is constant, in figure 7.6 the set value of  $K_p$  is constant.



**Figure 7.5** – Backlash detections as a function of the set value of  $K_p$ . The true value of  $K_p$  is 4 in all simulations. Note that each “detection” corresponds to a median/mean filtered set of detections over 1000 seconds.



**Figure 7.6** – Backlash detections as a function of the true value of  $K_p$ . The set value of  $K_p$  is 4 in all simulations.

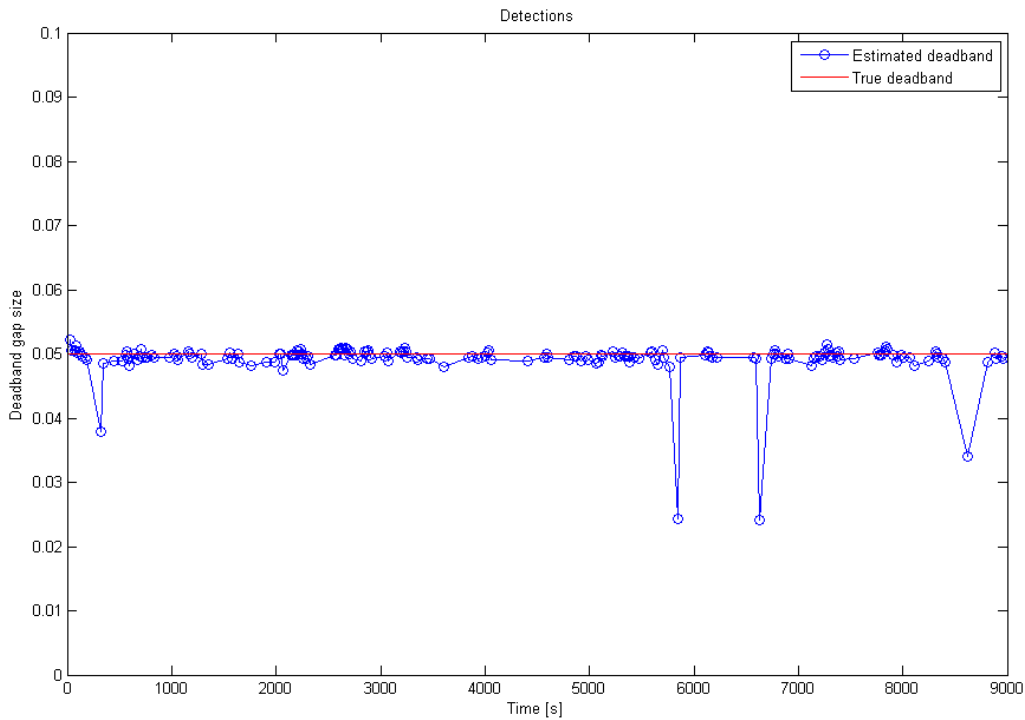
From figure 7.5 it can be concluded that setting the  $K_p$  parameter very low can lead to very small detections, even less than zero in the extreme case. In this set of simulations, a too high value of  $K_p$  leads to even better detections than the correct value. Figure 7.6 indicates that if the set value of  $K_p$  is large enough, a change of the true  $K_p$ -value must be very large before affecting the estimations. It should be noted that no value of  $K_p$  leads to too large backlash estimates in these simulations. Therefore, the value of  $K_p$  can never lead to an over compensated system, which is an important conclusion for the methods robustness.

### 7.3 Filtering of detections

The procedure described in [4] calculates a backlash estimate every time a zero-crossing occurs if the safety net conditions from chapter 5 are fulfilled. These estimates will hopefully be reasonably similar, indicating that the estimates are of good quality. Regardless of how similar the estimates are, only one value should be displayed to the operator for the method to be functional and simple enough to be used. To simply display the mean value of all previous detections is a possibility, but one with several flaws.

Chapter 5 defines a set of conditions designed to assure that detections are only calculated when there is a backlash behavior in the control loop. These conditions have been proved efficient in simulation, but when running the method online anything can happen. When something indeed does happen, meaning that a detection is calculated under non-typical circumstances, the calculated

backlash estimate will mostly often be far from the estimates calculated under normal conditions. Figure 7.7 shows a set of detections from a simulation where some detections are clearly erroneous.



**Figure 7.7** – Backlash estimates over time.

The deviating detections in figure 7.7 will affect the mean value. Preferably, deviating detections should not in any way be allowed to influence the mean value. This can be achieved using a median filter approach [9]. A median filter is a non-linear digital filter with good noise suppression properties. The median filter value can be generally defined as:

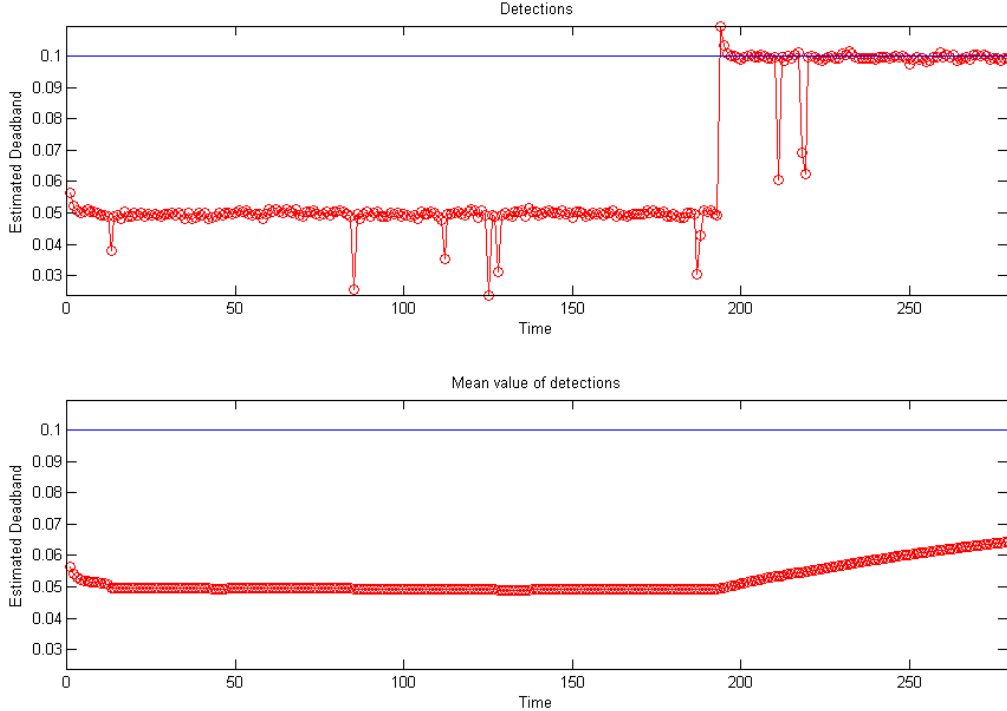
$$y(k, N) = \text{median} \left( x \left( k + \frac{N}{2} \right), x \left( k + \frac{N}{2} - 1 \right), \dots, x(k), \dots, x \left( k - \frac{N}{2} + 1 \right), x \left( k - \frac{N}{2} \right) \right),$$

where  $N$  is the size of the filter window. This implementation is not optimal for the backlash estimates since no detected value is probable to be exact. However, the median filter idea can be used to eliminate deviating detections like the ones in figure 7.7. The filter used in the remainder of this master thesis has the following properties:

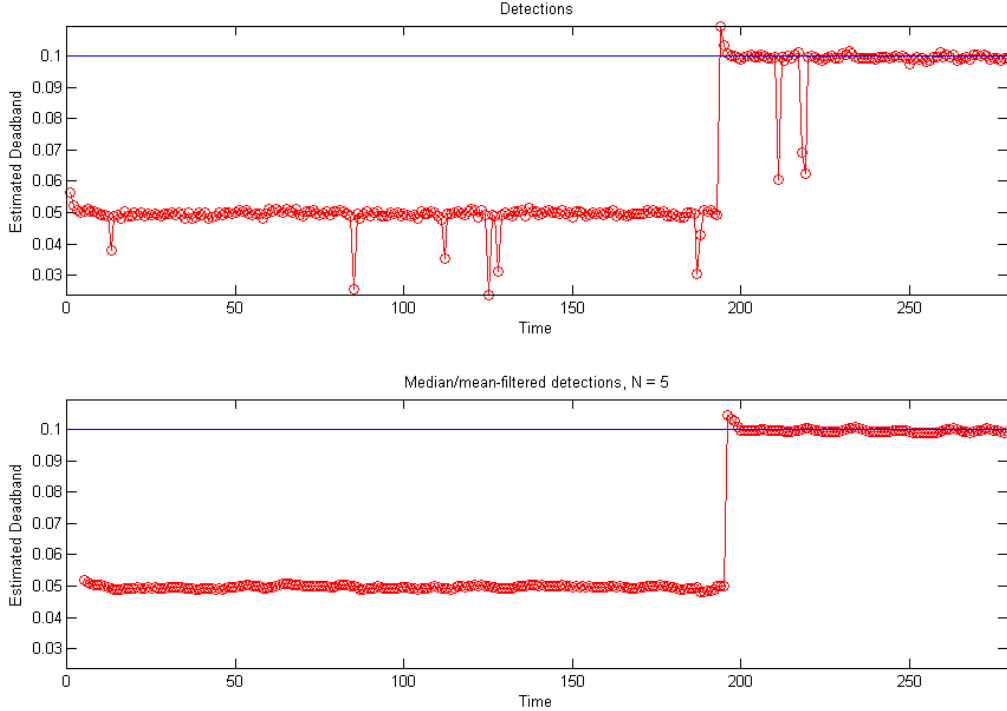
1. The median of the  $N$  last detections is calculated
2. All detections larger than 120% or smaller than 80% of the median are discarded
3. The mean value of the remaining detections is calculated and displayed

This filter provides a robust dead band estimate, uninfluenced by deviating detections. The filter size,  $N$ , could be set by the operator during operation or static. As  $N$  detections need to be made for a value to be displayed, a large value of  $N$  results in a delay. On the other hand, a small filter size can lead to unsmooth filter output as the median is calculated from fewer estimates. Figure 7.8 indicates

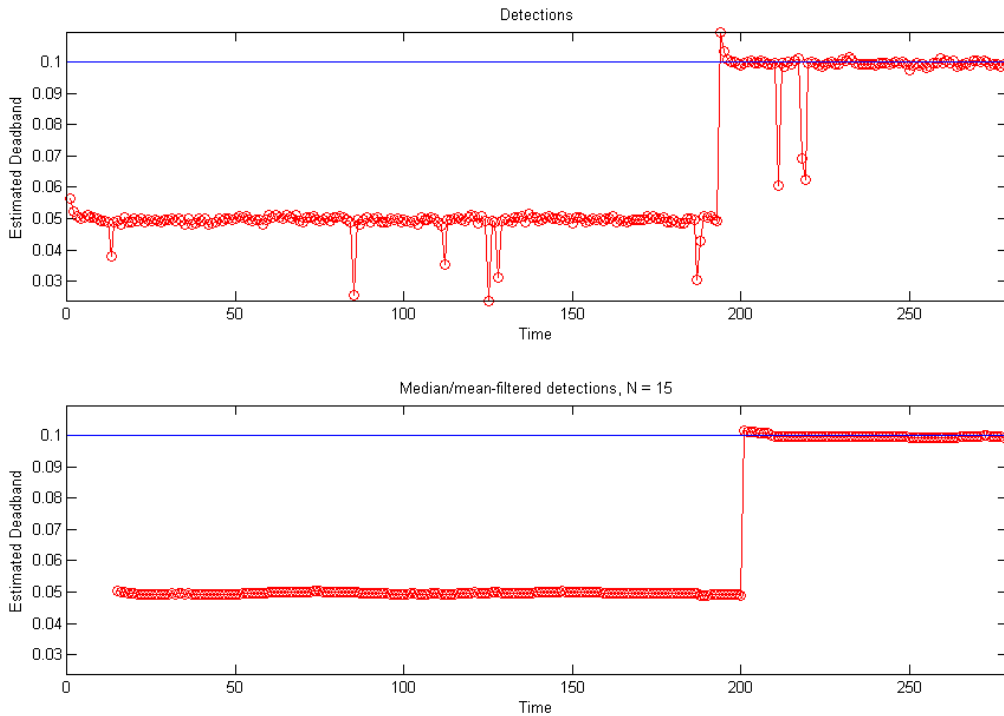
the drawback of pure mean filtering, while figures 7.9 and 7.10 highlight the influence of the filter window size  $N$ .



**Figure 7.8** – Mean value of detections. The sudden change of estimate magnitude affects the mean value slowly.



**Figure 7.9** – Median/mean filtering with filter window size  $N=5$ . The delay is short, but the filter output could be smoother.



**Figure 7.10** – Median/mean filtering with filter window size  $N=15$ . Longer delay than with  $N=5$ , but smoother filter output.

From figure 7.10 it is clear that a large value of  $N$ , in this case  $N=15$ , leads to a delay. It is on the other hand not very likely that the backlash estimates would change in such a sudden way as in these figures. In the implemented version of the filter, a filter width of  $N=9$  is used.  $N$  should always be an odd number, otherwise the median value is calculated as a mean value of the two most centered estimates, which can lead to that no estimate is within 80% and 120% of the median.

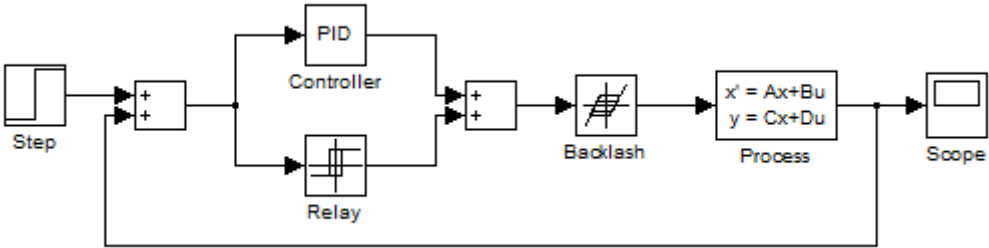
## 7.4 Over compensation detection

By compensating for a backlash the mechanical parts in the process can be used for a longer time before they have to be replaced or repaired, which is important for economical reasons. As discussed in 2.2, the compensation procedure is implemented by jumping trough the dead band every time the control signal is reversed. The feed forward signal,

$$u_{FF} = \frac{\delta}{2} \text{sign}(e),$$

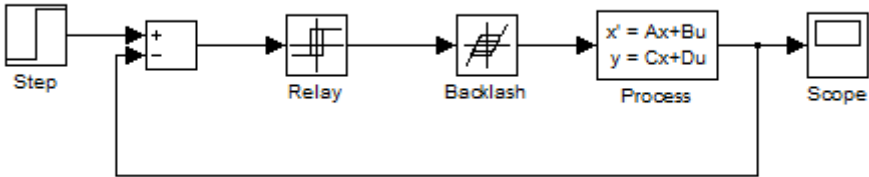
to the controller is implemented as an additional function to the estimation procedure. The user can choose to compensate for the entire amount of the estimated dead band or only parts of it. Compensating for less than the real dead band results in an under compensation and does not eliminate the typical backlash behavior in the control loop. The amount of backlash is reduced, but

not eliminated when under compensated. When over compensated, the controller can be modelled as a linear PID-controller and a nonlinear part caused by the compensation from the feed forward input, see figure 7.11. The nonlinear part can be described as a relay, with amplitude depending on the size of the over compensation. If the over compensation is large the relay is dominating the system, which can cause a limit cycle to arise.



**Figure 7.11** – A controller modelled as a linear PID-controller and a nonlinear part described as a relay when over compensated.

Since the dominating reason for the limit cycle is the relay part, the controller is removed as in figure 7.12 for an analysis of the system.



**Figure 7.12** – The controller is removed for an analysis of the system.

A relay followed by a backlash equals a relay with lower amplitude since the control signal from the relay has to drift through the dead band when reversed, that is

$$A_{relay} = \frac{compensation - deadband}{2}$$

A possible limit cycle will arise if the negative inverse of the describing function of a relay and the Nyquist diagram of the process intersect. The describing function of a relay is rather simple, and real

$$N(A) = \frac{4A_{relay}}{\pi A}$$

For a complete analysis the process must be known, however, this is not the case in the backlash estimation procedure. The negative inverse of the describing function of a relay can be seen in a Nyquist diagram as a line from zero to minus infinity. All processes with a Nyquist curve crossing the negative real axis will therefore cause a possible limit cycle, with unknown amplitude and frequency, when over compensated. All stable systems with pole excess larger than two (number of poles – number of zeros) or with time delay will have such a Nyquist curve. When compensation is active, limit cycles can be detected and warned for in a rather simple way. By comparing the time period for



zero crossings, oscillations with a constant frequency can be detected. The system oscillates if the time periods between the zero crossings are constant, that is  $\Delta t = \Delta t_1 = \Delta t_2 = \dots = \Delta t_n$ . If the maximum difference between the four last  $\Delta t$  is less than two times the sample rate when compensation is active, an indicator is shown in the interaction window. The over compensation method is implemented as

```

if max( $\Delta t_{i+3}$ ,  $\Delta t_{i+2}$ ,  $\Delta t_{i+1}$ ,  $\Delta t_i$ ) - min( $\Delta t_{i+3}$ ,  $\Delta t_{i+2}$ ,  $\Delta t_{i+1}$ ,  $\Delta t_i$ ) < 2h then
    OverCompensationWarning := true;
end_if;

```

**Code block 7.1** – Implementation of over compensation warning.

This is an effective method that also works on-line if the last four  $\Delta t$  are being saved.

## 7.5 Derivative action

In process industry, as much as 97% of the control loops use PI-control [7]. Of the remaining three percent, some are controlled with state feedback controllers, some with adaptive controllers, some with PID-controllers and so on. The procedure analyzed in this master thesis is implemented for use with a PI-/PID-controller, as this is clearly the most common case. To prove that the algorithm is applicable for PID-controllers, some questions must be answered.

The backlash detection algorithm estimates the dead band based on how much the control signal has changed between two zero crossings. This change,  $\Delta u$ , can be written as:

$$\begin{aligned}
 \Delta u &= u_{i+1} - u_i = \\
 &= K \left( -y_{sp} + \frac{1}{T_i} \int_0^{i+1} (y_{sp} - y_f) dt - T_d \dot{y}_f(i+1) \right) - K \left( -y_{sp} + \frac{1}{T_i} \int_0^i (y_{sp} - y_f) dt - T_d \dot{y}_f(i) \right) = \\
 &= \frac{K}{T_i} \left( \int_i^{i+1} (y_{sp} - y_f) dt \right) - K T_d (\dot{y}_f(i+1) - \dot{y}_f(i)),
 \end{aligned}$$

if a PID-controller on the form (4.1) is used. The integral part can then be rewritten, using the average error instead of the integral:

$$\Delta y \Delta t = \int_i^{i+1} (y_{sp} - y_f) dt.$$

If the controller is a pure PI-controller, we get the expression:

$$\Delta u = \frac{K}{T_i} \Delta y \Delta t. \tag{7.5}$$

If there is derivative action in the controller however, this expression is not true. In the original paper by Tore Hägglund the contribution from the derivative part of the controller is neglected, and  $\Delta u$  is

approximated as expression (7.5) regardless of if there is derivative action present. With derivative action,  $\Delta u$  is given by equation (7.6):

$$\Delta u = \frac{K}{T_i} \Delta y \Delta t - K T_d (\dot{y}_f(i+1) - \dot{y}_f(i)). \quad (7.6)$$

It must be shown that expression (7.6) is almost the same as expression (7.5). To start with, the derivatives are approximated as of equal magnitude but alternating signs:

$$|\dot{y}_f(i+1)| = |\dot{y}_f(i)| \rightarrow (\dot{y}_f(i+1) - \dot{y}_f(i)) = \pm 2 |\dot{y}_f(i)| \rightarrow$$

$$\Delta u = K \left( \frac{\Delta y \Delta t}{T_i} \pm 2 T_d |\dot{y}_f(i)| \right).$$

$$|\dot{y}_f(i)| = \left| \frac{\Delta y_f}{\Delta t} \right| = \left| \frac{\Delta y_f}{\Delta u} \cdot \frac{\Delta u}{\Delta t} \right|,$$

but by assuming that the signals are changing slowly the process dynamics can be neglected, and  $\Delta y_f = K_p \Delta u$ :

$$|\dot{y}_f(i)| = \left| K_p \cdot \frac{\Delta u}{\Delta t} \right|,$$

and thus:

$$\Delta u = K \left( \frac{\Delta y \Delta t}{T_i} \pm 2 \cdot T_d \cdot K_p \cdot \frac{\Delta u}{\Delta t} \right) \rightarrow$$

$$\Delta u \left( 1 \pm \frac{2 \cdot K \cdot T_d \cdot K_p}{\Delta t} \right) = \frac{K}{T_i} \Delta y \Delta t.$$

It must now be shown that:

$$\frac{2 \cdot K \cdot T_d \cdot K_p}{\Delta t} \ll 1.$$

The derivative gain  $T_d$  is never larger than  $T_i/4$ , if the controller is properly tuned. For example, the Autotuner always sets  $T_i = 6.25 T_d$  [10], and the Ziegler-Nichols methods sets  $T_i = 4 T_d$  [5]. It is also known that the zero crossing period  $\Delta t > 5 T_i$ . Inserting this gives:

$$\frac{2 \cdot K \cdot T_d \cdot K_p}{\Delta t} < \frac{2 \cdot K \cdot T_d \cdot K_p}{5 \cdot 4 \cdot T_d} = \frac{2 \cdot K \cdot K_p}{20}.$$

As stated in equation (7.4), the product  $K_p K$  is limited between 0.5 and 1. This proves that in the worst case,

$$\frac{2 \cdot K \cdot T_d \cdot K_p}{\Delta t} < \frac{2}{20} = 10\%,$$

which means that the error caused by the approximation:

$$\Delta u \approx \frac{K}{T_i} \Delta y \Delta t$$

is less than 10%. With this being proved, it is safe to use the approximation in the backlash estimation algorithm.

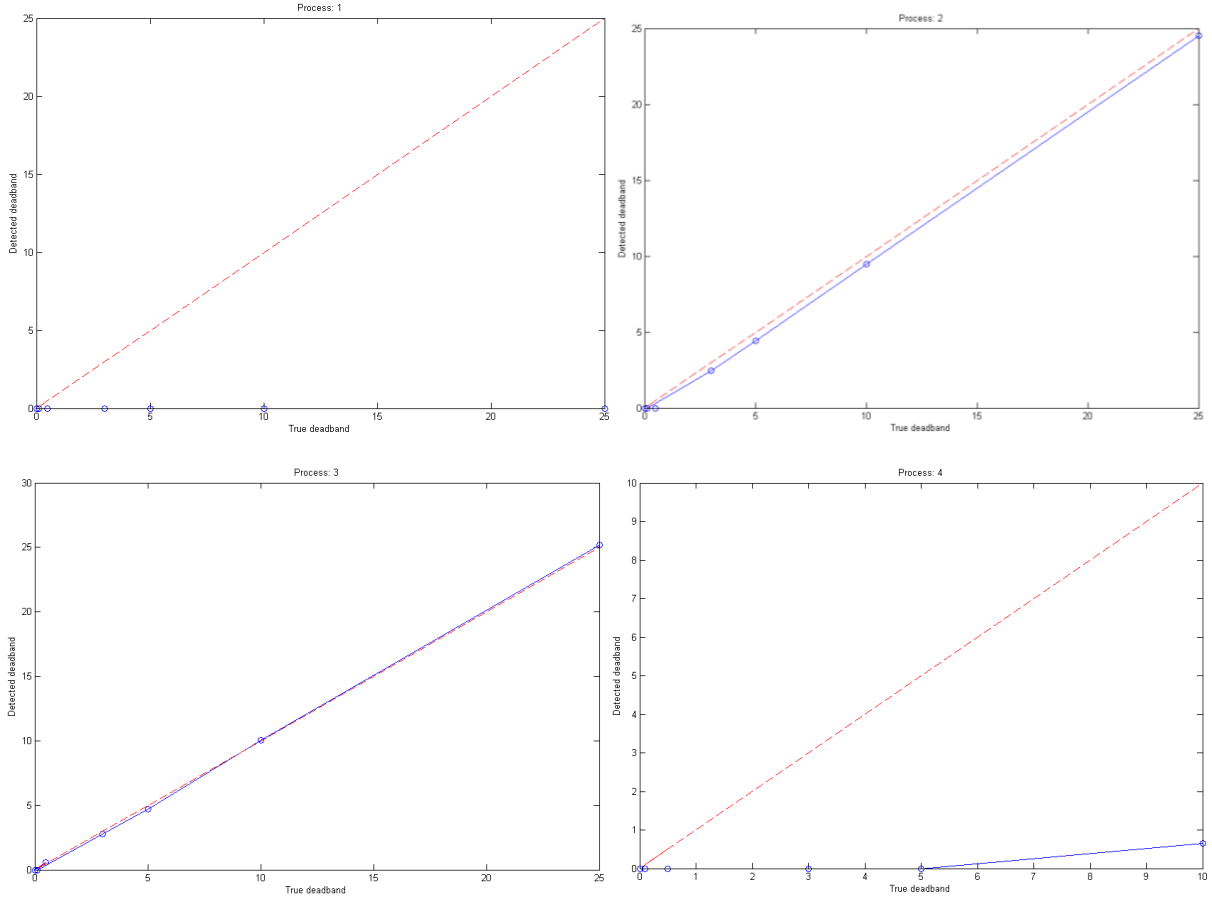
It should also be mentioned that the error caused by the approximation is alternating between positive and negative, with similar magnitude. The filter defined in section 7.3 will therefore smoothen the error out.

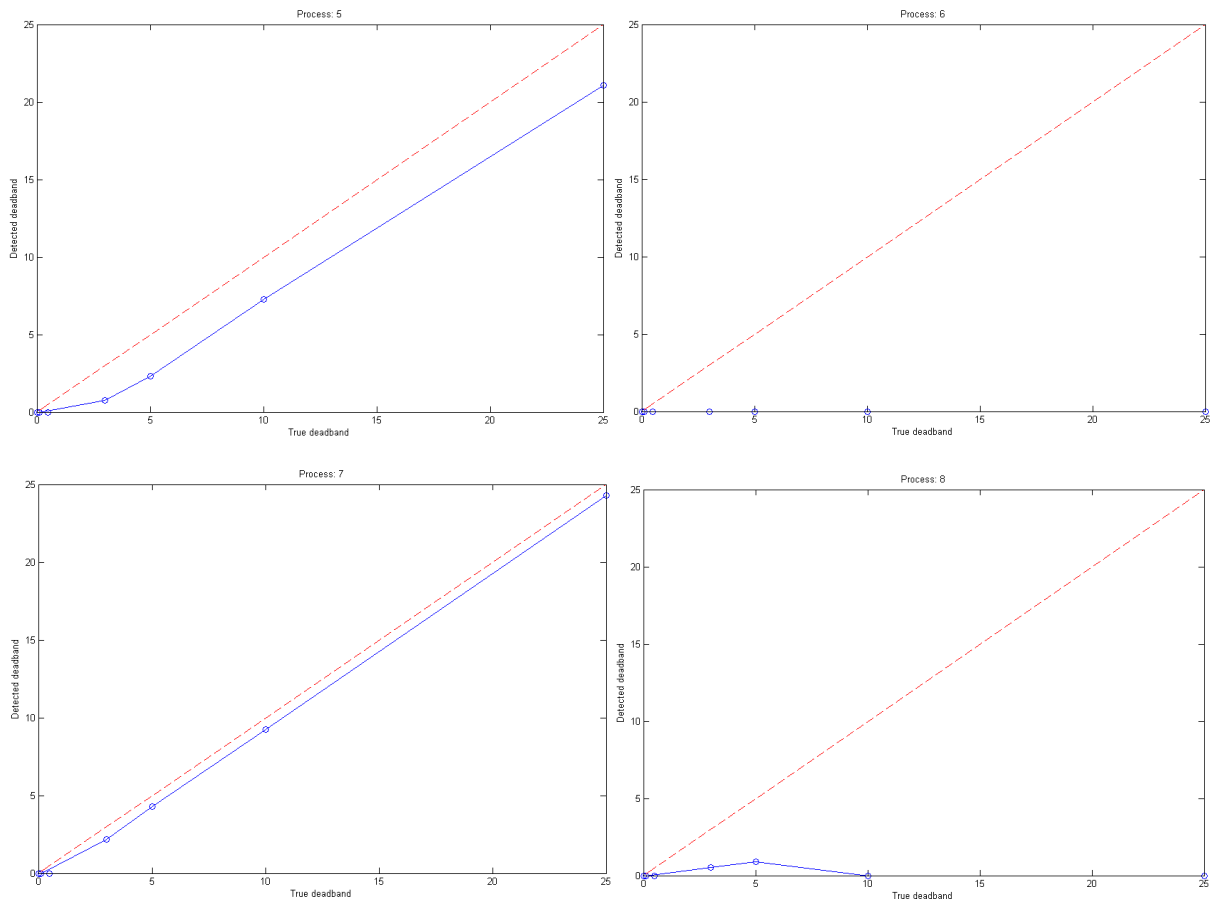
# 8. Testing

*The only way to guarantee the robustness of the backlash estimation procedure and find out if the safety net is sufficient is by performing tests and simulations. In this chapter different tuning methods, cascaded control and systems with dead time are tested. Simulations on all processes in the test batch are performed and finally real industrial tests are made.*

## 8.1 Test of test batch

The test batch contains eight different processes, all suitable for PID-controllers. Lag dominated, delay dominated, balanced and integrating processes have all been tested with the backlash estimation procedure with satisfying results. All processes are controlled with PI-/PID-controllers with controller parameters obtained from the MIGO tuning rules. Simulations with various dead bands are made on the processes and presented in figure 8.1.





**Figure 8.1** – Simulations of all processes in the test batch with various dead bands. The dashed line (red) corresponds to a correct dead band estimation and the solid line (blue) the median filtered dead band estimate.

The figures above correspond to the eight processes in the test batch simulated with various dead bands. The red dashed line in the figures represents a perfect estimation, in other words when the estimated dead band equals the true dead band. The solid blue line corresponds to the actual estimations obtained with the backlash estimation procedure. The simulations show that the estimations are slightly lower than the true dead band or equal to zero for all processes in the test batch. This is a good property, since it is important that the backlash compensator does not use an estimate that is too high.

The fact that no detections are made for several processes is caused by the lack of backlash behavior in the process value. The first process  $P_1$  is an integrating process that causes a limit cycle to arise if backlash is present in the control loop.  $P_4$  is a system with significant time delay and  $P_8$  a delay-dominated process, both hard to control. This results in restrained controller parameters with less impact on backlash and as a result less detections. The backlash estimation procedure provides in general satisfying results and works on-line for all processes in the test batch.

## 8.2 Tuning Methods

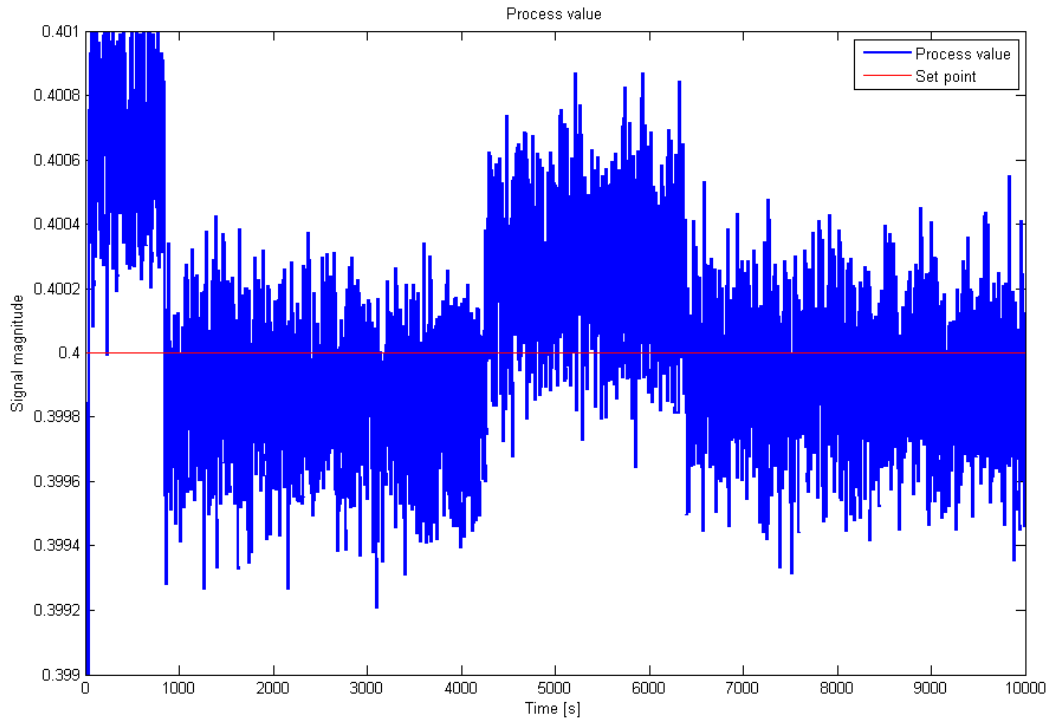
Different types of tuning methods and controllers provide dead band estimates with various accuracy. By choosing an advanced tuning method, the detections obtained from the estimation procedure can be drastically improved. A number of simulations, with various controllers and tuning methods, are presented in table 8.1. The simulations are made on process  $P_2$  from the test batch with a dead band of 5% during 5000 seconds.

$P(s) = \frac{1}{(1+s)^4}$ <b>d = 5%</b>	Estimated d (%) / Number of detections	Estimated d (%) / Number of detections
	PI	PID
Ziegler-Nichols frequency	4,22 % / 8	2,79 % / 55
Lambda	---	4,49 % / 3
MIGO, M=1.4	---	4,39 % / 77
AMIGO step.	---	3,90 % / 39
AMIGO frequency	---	4,10 % / 77

**Table 8.1** – Simulations during 5000 seconds with various controllers and tuning methods.

The table shows that the backlash estimation procedure works with all tuning methods. Ziegler-Nichols is a rather aggressive procedure and provides the least accurate results, but is still precise for its simplicity.

The low number of detections when using Lambda tuning is not a coincidence. The slow, or *sluggish*, control obtained from the Lambda tuning results in long zero crossing intervals when there is backlash present in the loop. This is a direct effect of the controller tuning, as the time it takes to drift through the dead band is proportional to the quotient  $T_i/K$ . As table 8.1 shows, the detections made with a Lambda tuned controller are the most precise. As the zero crossing periods are long, the effects of round off and noise are minimized. These characteristics – few but accurate detections – are typical for slow controllers. However, if the controller is too slow, the amount of detections can be reduced to zero. Figure 8.2 shows the result from a simulation with a very sluggish controller.

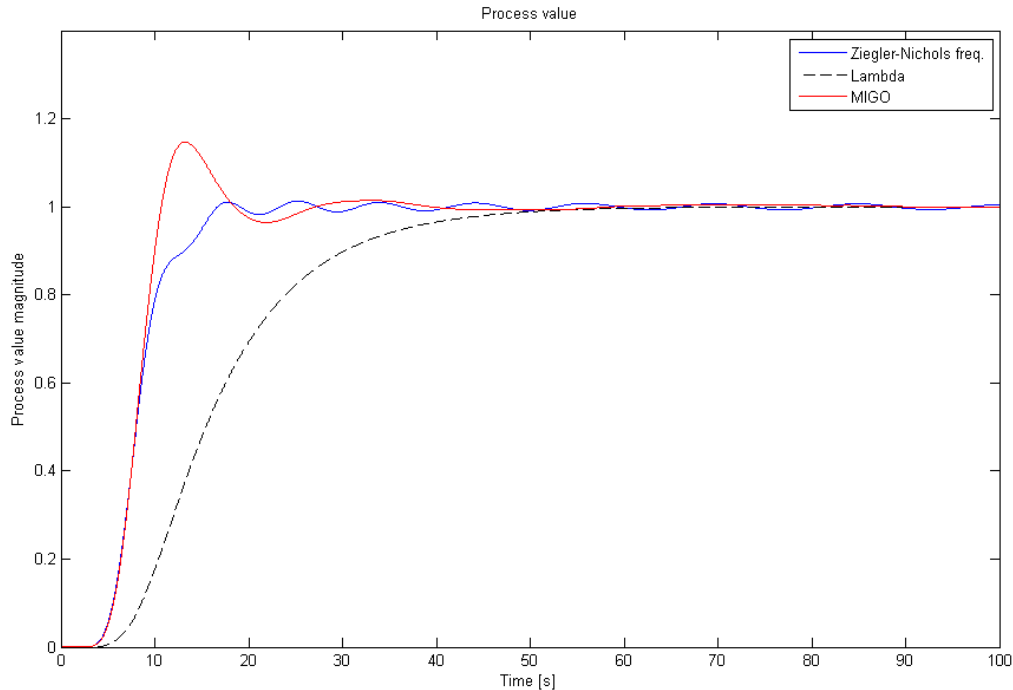


**Figure 8.2** – Simulation with very sluggish controller during 10 000 s. The process value is always close enough to the setpoint for the noise to cause zero crossings.

As figure 8.2 clearly shows, the average control error is smaller in magnitude than the noise. The average control error, denoted  $\Delta y$  throughout this thesis (see figure 2.1), can be seen as an overshoot that occurs when the backlash gap is crossed. If the controller is slow, the process value only changes a little before the control action is reversed. No detections are made during the simulation in figure 8.2, as the noise causes zero crossings that does not fulfill the zero crossing time interval condition defined in section 6.2. A possible solution to this problem would be to increase the feedback filter time,  $T_f$ , which by default is set as  $T_f = T_i/2$ .

The lack of detections when PI-control is used is caused by the lack of backlash behavior in the process value. This is directly related to the process and should not be seen as an overall conclusion.

Figure 8.3 shows process  $P_2$  being controlled with various tuning methods and with backlash in the control loop.



**Figure 8.3** – Step responses for process  $P_2$  obtained from various tuning methods with backlash in the control loop.

The simulation with the controller parameters obtained from the Ziegler-Nichols method, provided a large number of detections, but not very accurate ones. The tuning is, as figure 8.3 suggests, too poor to achieve desired closed loop behavior. It takes a very long period of static setpoint for the process value to stop oscillating. These oscillations affect the backlash estimation.

MIGO and approximate MIGO are both relatively advanced tuning methods that provide very good controllers which leads to accurate estimations. The methods result in many detections, where the estimation obtained from the approximate MIGO is slightly lower than for the original method.

## 8.3 Cascade control

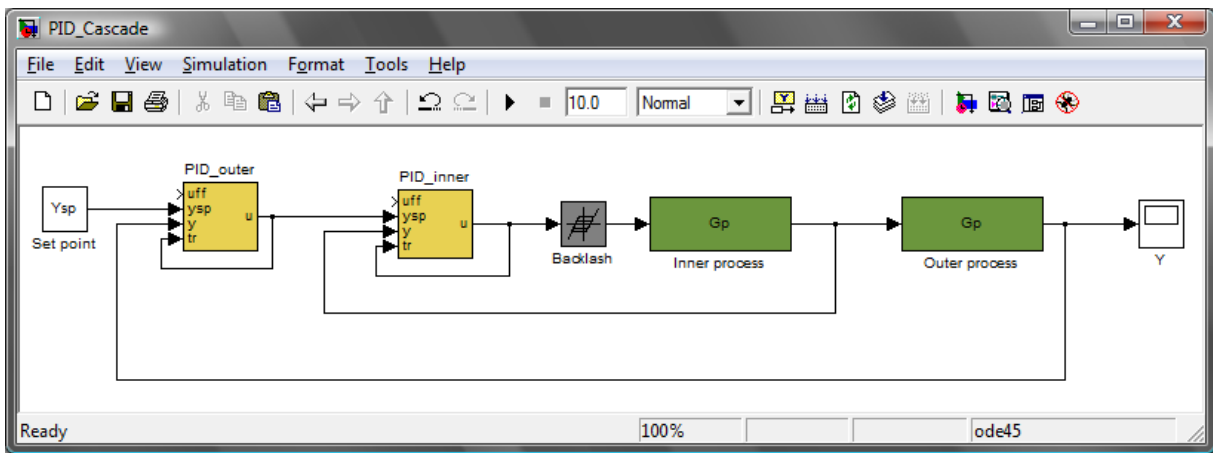
Some processes are difficult or impossible to control with a simple PI-/PID-controller [3]. In those cases, a more sophisticated control strategy is needed. If the process model is known, state feedback can be used to efficiently place the closed loop poles in their desired positions. Other strategies include model predictive control and internal model control. In process industry, it is a rarely seen luxury to be in possession of an exact model of the process to be controlled, why it is impossible to use these model based control strategies. Even so, the concept of state feedback can be used with well tuned PI-/PID-controllers to obtain a stable system. This results in a cascade control system, where one controller provides a setpoint for the next one. In order to use cascade control, the process must be dividable into two or more parts, and the process value must be measurable in each junction. If the measurable signals corresponds to the state variables, cascade control is in fact equivalent to state feedback [3], and as such, the closed loop system poles can be placed arbitrarily under the assumption that the process is controllable [5].



### 8.3.1 Backlash on the input of the inner process

If cascaded control is used, the reference to the “process input” becomes ambiguous. As the process model is split into two or more parts, each with both an input and an output. The parts can be separated into being either an *inner* or an *outer* process. The fundamental difference lies in the fact that inputs of inner processes are directly connected to a controller, while as outer processes receive their input signals from the output of another process. There can only be one inner process in a cascade control system, but the number of outer processes are unlimited.

Figure 8.4 shows a Simulink model of a two-stage cascade control system with backlash on the inner process input.



**Figure 8.4** – Two stage cascade control loop in Simulink. The inner process is subject to backlash on the input.

It is of interest to find out how the detection algorithm handles backlash in a cascaded control loop. To test this, process  $P_2$  from the test batch,

$$P_2 = \frac{1}{(s + 1)^4},$$

is rewritten as two processes,

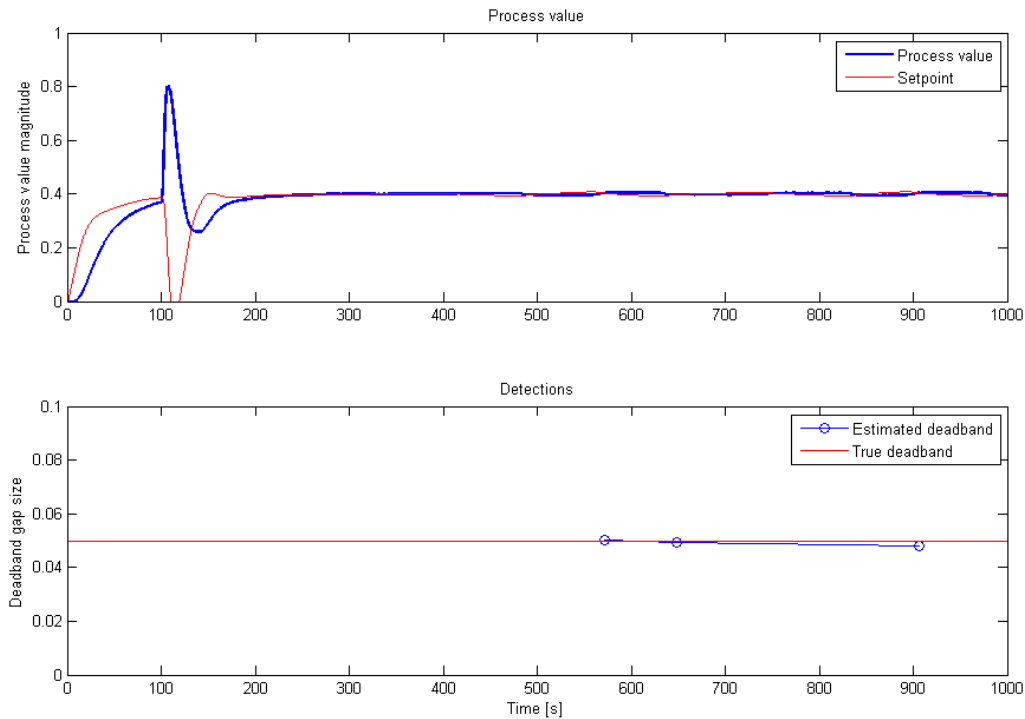
$$Gp_1 = \frac{1}{(s + 1)^2},$$

$$Gp_2 = \frac{1}{(s + 1)^2},$$

such that

$$P_2 = Gp_1 \cdot Gp_2.$$

Now, process  $P_2$  can be controlled using cascaded control. Note that the controller parameters have to be recalculated to provide satisfactory closed loop behavior. Simulation of the cascaded system with a step reference and load disturbance at  $t=100$  s is given in figure 8.5.

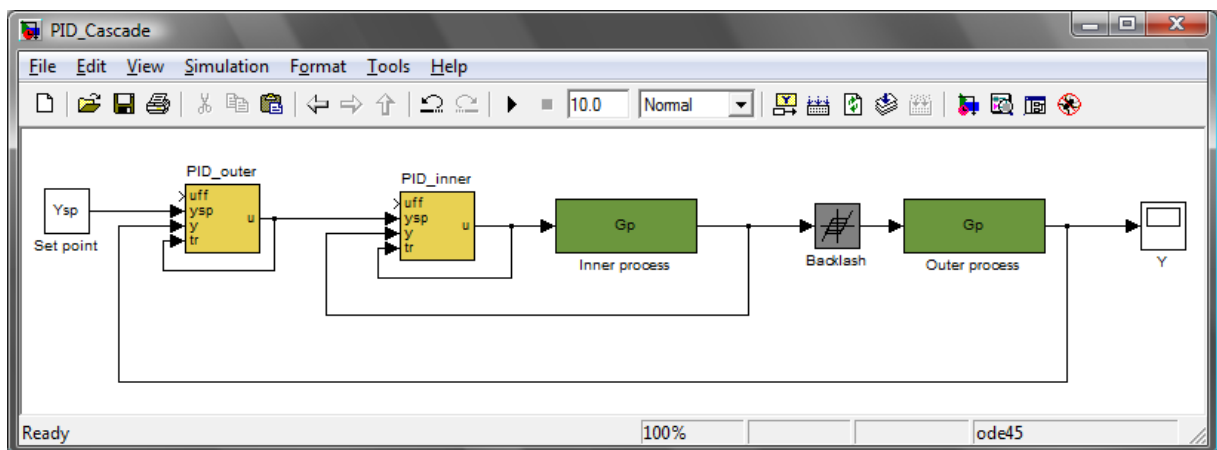


**Figure 8.5** – Detections made in the inner loop with cascaded control.

Clearly, the detection algorithm can be used in the inner loop with cascade control. In this case, the only effect of using several controllers is that the setpoint delivered to the inner loop is set by a controller.

### 8.3.2 Backlash on the input of an outer process

When backlash is present on the input of the secondary process  $G_{p2}$ , the system can be modeled as figure 8.6.



**Figure 8.6** – Simulink model of a cascaded control loop with backlash on the outer process input.

The backlash detection algorithm estimates the dead band based on the amount  $\Delta u$  needed to change the process value enough to make the control error change sign. When there is a control loop

between the outer controller and the backlash, the control signal is distorted before it reaches the backlash. Because of this, it is impossible to make an accurate estimation of the backlash, as the input to the backlash cannot be predicted. This insight states a fundamental limitation of the detection procedure; detections can only be made in the inner loop of a cascade control system.

Fortunately, it is not very likely that backlash is present on the input of the outer process. Typically, in process industry, the inner process is a valve while the outer is a tank, and it is the valve that is affected with backlash.

## 8.4 Dead time

In industrial control systems, time delays are always a problem. Time delay, or *dead time*, can be caused by long signal paths, feedback loops, computation time etc. These signal related dead times are however very short compared to physical ones, such as the time it takes for a flow of paper mass to reach from a newly opened valve to the tank level. In the worst case, these dead times can be as long as minutes or hours.

### 8.4.1 Dead time and backlash

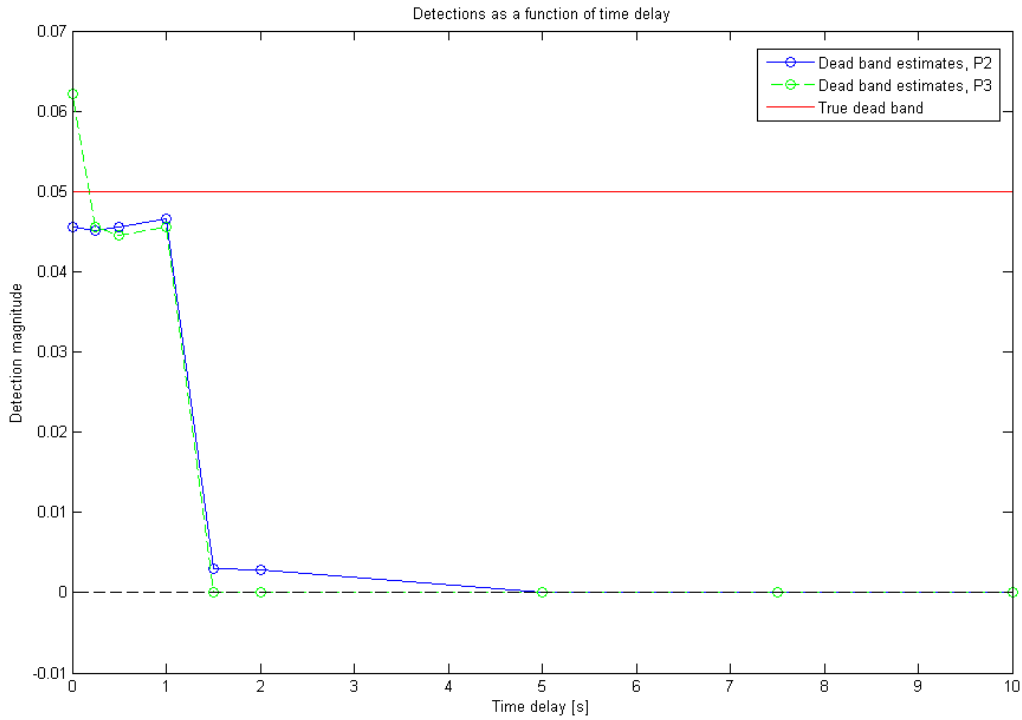
In a sense, backlash can be seen as a special type of time delay. The delay is not constant, and only shows when the control signal changes direction, e.g. from increasing to decreasing. As a large backlash leads to longer delay times, it is not unreasonable to suspect that internal process dead times can affect the estimated backlash.

Figure 8.7 shows how backlash estimates relate to the process dead time. In the simulations, process  $P_2$  and  $P_3$  from the test batch is used, with added time delay, that is:

$$P_{2+delay}(s, L) = \frac{1}{(s+1)^4} e^{-sL},$$

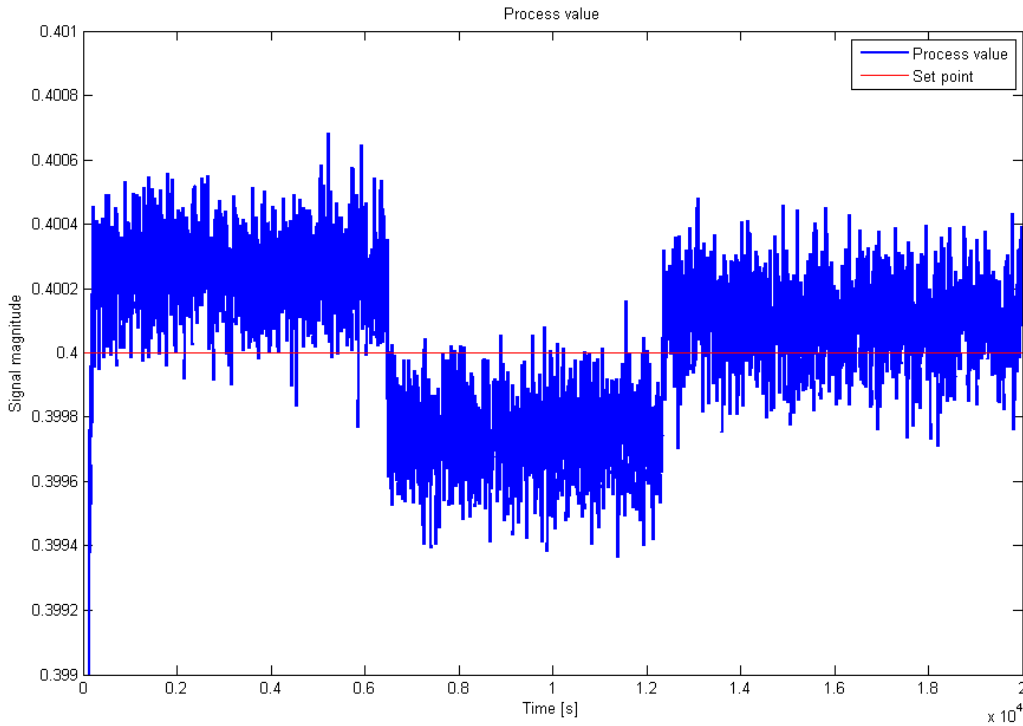
$$P_{3+delay}(s, L) = \frac{9}{(s+1)(s^2+2s+9)} e^{-sL},$$

where  $L$  is the time delay in seconds. The controller parameters have been recalculated for every value of  $L$ , using the software designPID [8], to eliminate the effects of improper tuning.



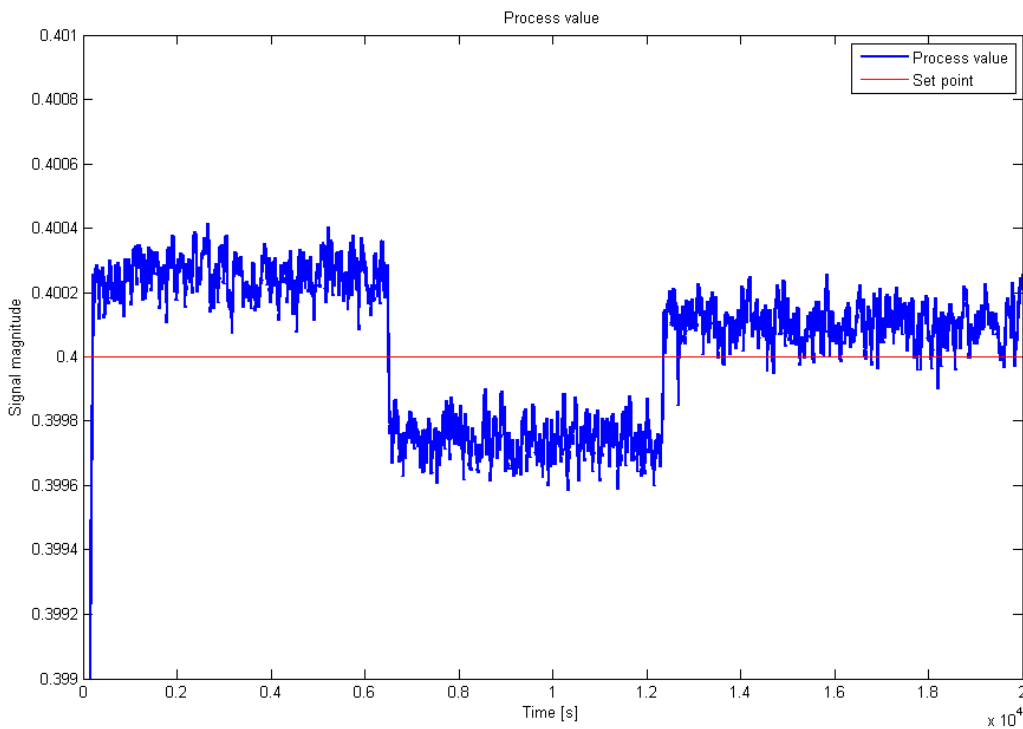
**Figure 8.7** – Average backlash estimates as a function of process time delay  $L$ .

From figure 8.7 it can be concluded that dead time affects the estimation procedure considerably. For long time delays, no detections are made at all. This is a fact since the controller is tuned to be very moderate not to risk the closed loop stability when there is a long time delay within the process. In section 8.2 it was shown that too sluggish control leads to a loss detections. This is why no detections are made when there is a long time delay in the system. Figure 8.8 shows how the process value behaves in a 20 000 seconds long simulation with 15 seconds delay on the process input.



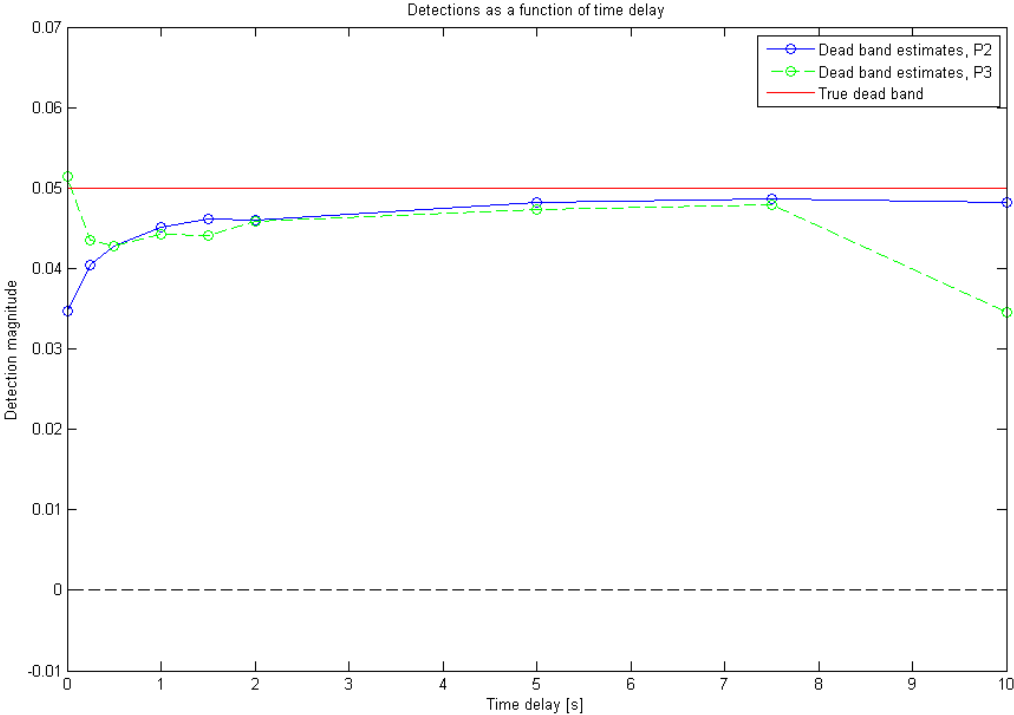
**Figure 8.8** – Process value with long dead time

As discussed in section 8.2, a change of filter time constant  $T_f$  could solve this problem. Figure 8.9 shows how an increase of filter time constant with a factor 4 affects the process value.



**Figure 8.9** – Process value with increased filter time constant, compare with figure 8.8.

As figure 8.9 shows, a change of filter time constant solves the problem, and a dead band detection is made at  $t \approx 12500$  s. The estimated dead band is calculated as 0.04817, which is very close to the true value, 0.05. If the filter constant  $T_f$  is calculated as  $2T_i$  instead of  $T_i/2$ , the simulations with different process input delay times from figure 8.7 instead results in figure 8.10.



**Figure 8.10** – Dead band estimates with increased filter constant  $T_f$ . Compare with figure 8.7.

Figure 8.10 shows that the dead band estimation method works perfectly well with process dead time, under the assumption that the filter constant  $T_f$  is chosen wisely. In fact, long dead time and correspondingly sluggish controller tuning leads to surprisingly accurate dead band estimates.

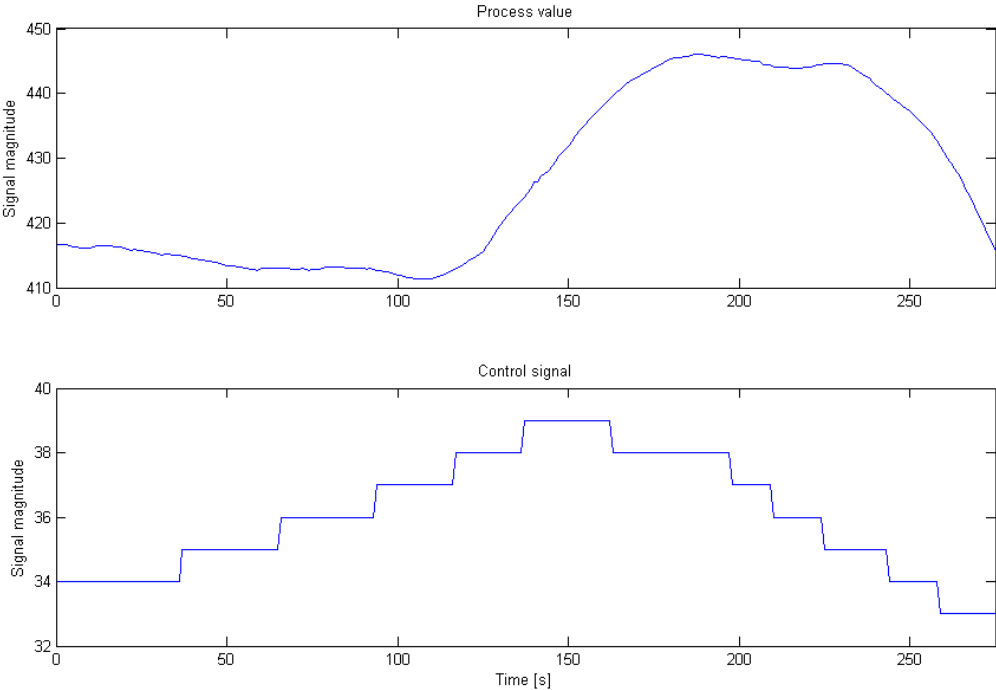
## 8.5 Industrial tests

Measured data from real industrial environment were collected and tested on the estimation procedure. Since the procedure only observes and consequently detects the backlash of the process and not changes any values, the measured data is just as good as real industrial tests. Process data obtained from Krister Forsman at Perstorp and from Hyltebruk were studied and presented. Manual tests are made to confirm the detections provided from the backlash estimation procedure.

### 8.5.1 Hyltebruk

The process section at Hyltebruk is a pipe where pulp is transported from a recycling pulp tower to a tank. A valve, controlled by a PI-controller, controls the pulp flow. The set of data from Hyltebruk contains an external setpoint that represents the wanted tank level downstream, the pulp flow  $\bar{y}$  and the controller output  $u$ ; everything needed for the estimation method and manual backlash tests to

operate. To check the amount of backlash in the valve, a manual test was performed and is presented in figure 8.11. When the control signal reaches its final value at  $u \approx 39\%$  the flow is increasing, which indicates that the gap is closed and the valve moves. The control signal is then reversed and drifts through the gap until the flow starts to decrease at  $u \approx 36\%$ . The test shows that the backlash is around 3%.

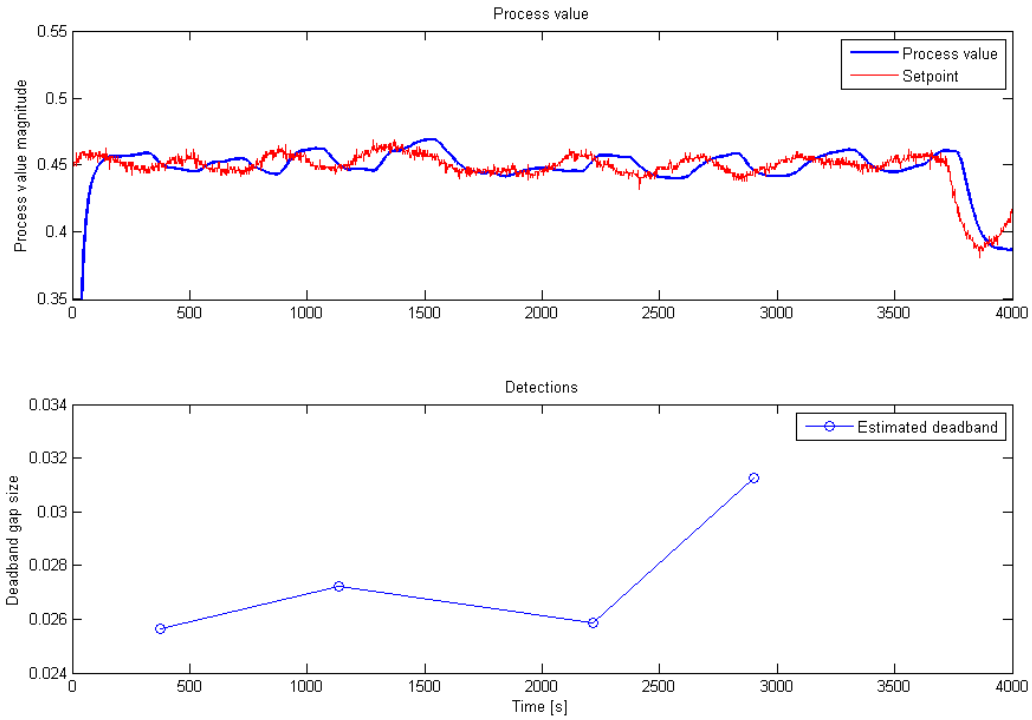


**Figure 8.11** – Process value obtained from a manually changed control signal.

The same figure can also provide the process static gain  $K_p$  in a similar way. By measuring the flow when a manual change of the control signal is performed, the gain can be calculated from

$$K_p = \frac{\Delta y}{\Delta u} \tag{8.1}$$

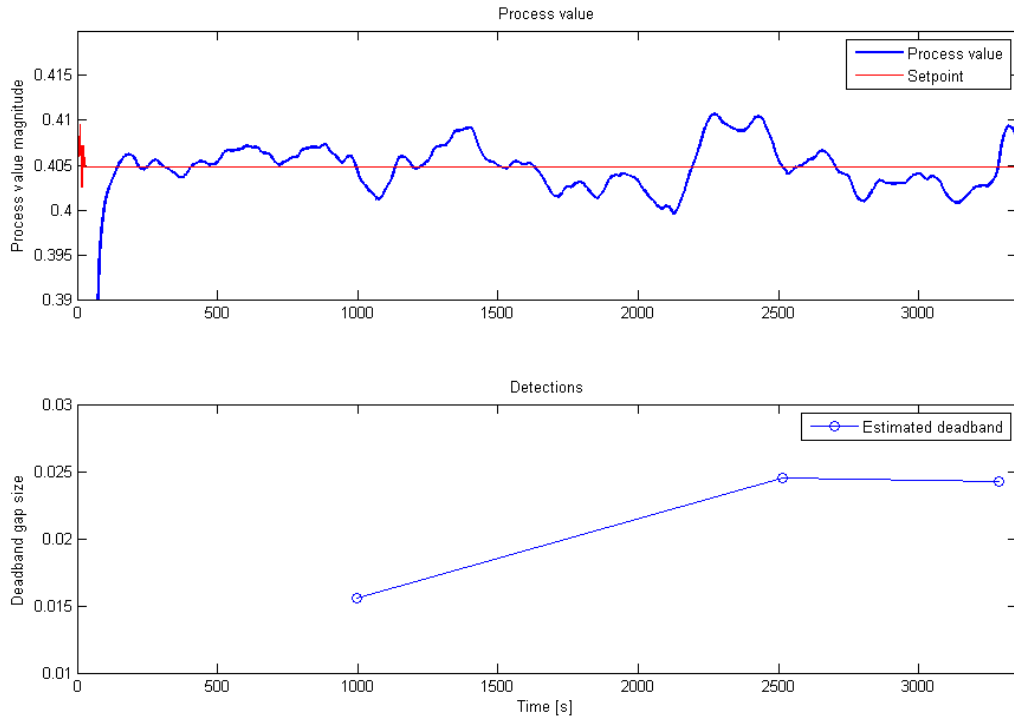
With the controller parameters  $K=0.6$ ,  $T_i=28$  s and the static gain estimated to  $K_p=1.3$  the backlash estimation procedure provided the results in figure 8.12. The loop is oscillating due to the external varying setpoint, probably generated by the backlash. Figure 8.12 shows that backlash was detected and estimated four times during the test, with values near the estimation obtained from the manual test.



**Figure 8.12** – Process value and estimated detections obtained with an external setpoint from Hyltebruk.

Experiments with an internal setpoint were also performed, to avoid setpoint variations that may disturb the backlash estimation. Figure 8.13 shows the results obtained with the internal setpoint, where the oscillations caused by the setpoint variations have disappeared. The three backlash detections made during the test are slightly lower than in the previous example. This can be expected since setpoint variations amplify the effect of the backlash.

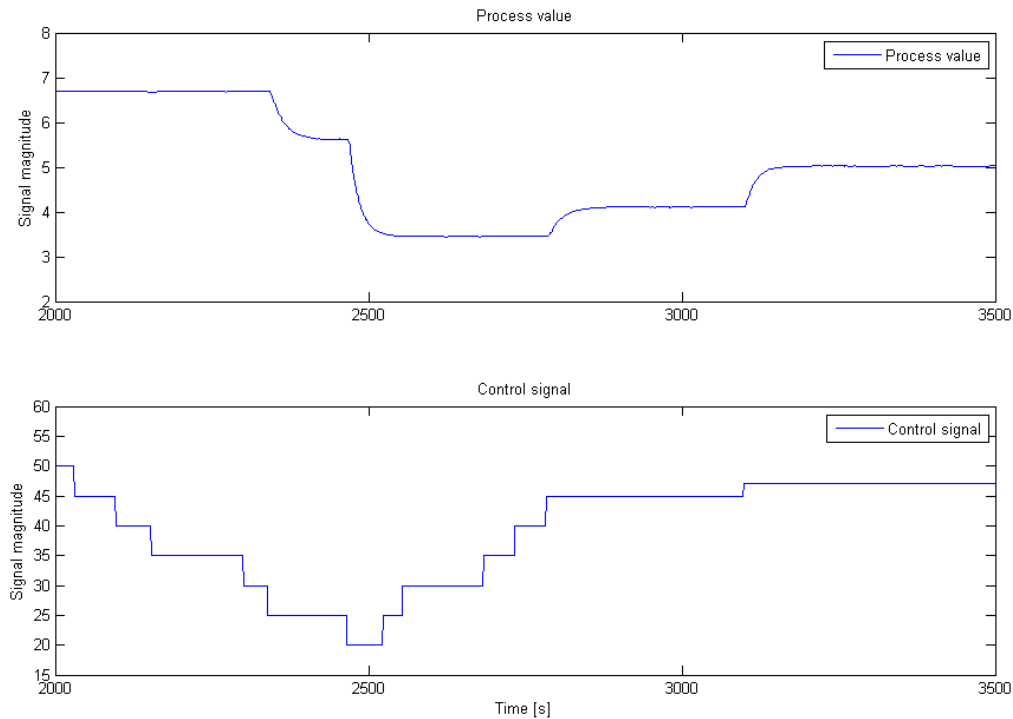




**Figure 8.13** – Process value and estimated detections obtained with an internal setpoint from Hyltebruk.

### 8.5.2 “Perstorp”

The process data obtained from Krister Forsman at Perstorp contains the setpoint value, the process value and the control signal, but the controller parameters and the static process gain  $K_p$  are not known. By using a MatLab script, designed by Krister Forsman, the controller parameters can be obtained from the process data only. The script provided a PI-controller with parameters  $K=8.5$  and  $T_i=10.3$  s. The estimation procedure requires the static gain of the process as well; this can be obtained from the process data, see figure 8.14.

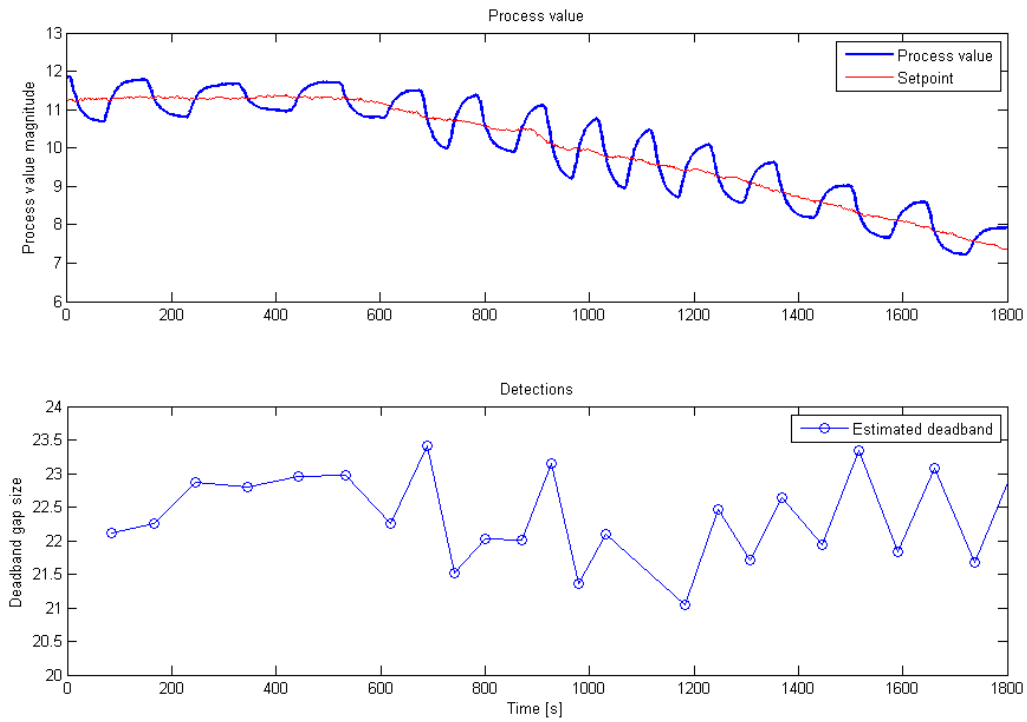


**Figure 8.14** – The process value obtained from a manually changed control signal.

Figure 8.14 shows a manually changed control signal. After  $t=2500$  s the control signal is reversed and drifts through the gap.  $K_p$  is then given by the step at  $t=3097$  s, see equation (8.2).

$$K_p = \frac{\Delta y}{\Delta u} = \frac{0.92}{2} = 0.46 \quad (8.2)$$

The backlash can be manually estimated in the same figure by observing the change in the process value over time. When the control signal is reversed at  $t=2500$  s, it takes another 300 s for the process value to change. The control signal drifts from 20 to 45 during the same time period, this indicates that the gap is around 25. The backlash estimation procedure, with the controller parameters  $K=8.5$ ,  $T_i=10.3$  s and the static gain  $K_p=0.46$ , provides the results in figure 8.15. Several detections are made and estimated around 22; the manually changed signal confirms the result.



**Figure 8.15** – Process value and estimated detections.

The results from the industrial tests confirm that the backlash estimation procedure works automatically in an industrial environment. By detecting and estimating the backlash on-line during a longer time period, a more accurate estimation can be obtained. The estimations provided by the manual tests are not as precise as the real detections, but still confirm the amount of backlash in the control loop.

## 9. Conclusions and future work

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*This chapter covers the main conclusions made during this project, which give answers to the initial objectives described in section 3.1. Future work that could improve the backlash estimation procedure is also studied.*

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The initial objectives, described in chapter 3, of the project have been answered and expanded in this thesis with satisfying results. The main contribution to the thesis has been to expand the safety net in order to achieve an as stable and secure backlash estimation procedure as possible. The method has passed a number of industrial tests, which also was one of the main project goals. Tests show that the method works as expected; automatic and on-line. The implementation part of the backlash procedure, made in Control Builder, was just as important since the method is intended for use in an ABB 800xA environment.

The original safety net consisted of two requirements; the time between zero crossings must exceed  $5T_i$  and the maximum error should not exceed two times the average error. The safety net has been expanded to obtain a robust procedure that is automatic in the sense that no user interaction is needed, which resulted in three additional requirements, namely:

An additional condition for the time period, where the time between zero crossings are inversely proportional to the average error,

$$\Delta t > \frac{T_i \hat{d}}{2K\Delta y}.$$

Condition for the curve form, essentially for detecting load disturbances and decaying oscillations,

$$0.5 < \left| \frac{\Delta y_{previous}}{\Delta y} \right| < 1.5.$$

Finally, a condition for changes in setpoint,

$$\Delta y_{sp} < \Delta y.$$

These conditions guarantee a robust backlash procedure that only calculates an estimate when backlash is present in the control loop.

The implementation in Control Builder of the backlash estimation procedure resulted in a stand-alone control module with optional backlash compensation. The control module is tested in an ABB 800xA environment with satisfying results. The method is currently implemented as a stand-alone control module, with the controller parameters and filter-time constant given by the user. In the future, the method could be implemented as part of an already existing controller, such as the PidCC or the PidAdvancedCC. This would simplify the use of the method, since no active decision whether or not backlash could be present in the process needs to be taken by the user.

In addition to these fundamental goals that focus directly on the detection method, functions that concern the execution and customer experience were added. For example, problems such as saturation and over compensation were investigated and solutions implemented to the method.

Effects of different tuning methods, cascade control, dead band and the static process gain  $K_p$  were also studied.

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