University of Alberta

Alarm Limits, Deadbands and Chattering

by

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Abstract

Receiving false and nuisance alarms is a well known problem in industrial alarm systems. The main cause of this problem is poor alarm design which is the result of huge number of configured alarms and lack of automatic and analytical design methods.

This study targets deriving analytical methods for designing alarm parameters such as alarm limits, alarm deadbands and delay timers. The relation between false and missed alarm rates along with chattering is investigated with alarm limits and deadbands. There are two equations presented to estimate the optimal alarm limit with respect to deadbands and statistical characteristics of the process data.

Since reduction of alarm chattering is a primary goal in redesigning the alarm parameters, the analytical relation between chattering with alarm parameters and process data is also investigated. The alarm chattering index is derived as a mathematical function of alarm limits, deadbands, time delays and statistical characteristics of the process data.

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1 Introduction and literature review

1.1 Introduction

Alarms are configured on every industrial plant as part of the monitoring system. The most important reason for monitoring industrial processes is safety. On average, a major incident occurs in petrochemical plants in every three years. In addition to human injuries that are usually occurring during these incidents, huge cost of repair and profit loss follow the incidents. By efficient monitoring of the plants it is possible to identify the abnormalities in the operation and act accordingly to keep the operation in its normal region. This can prevent simple malfunctions to develop into severe incidents.

Environmental issues are the other important reason for monitoring. Severe penalties are imposed to industries that exceed the environmental protection regulations. There are other important reasons for plant monitoring such as the quality of the product and preventing equipment problems and unplanned shut downs.

Due to these reasons alarm systems are designed to inform the plant operators of abnormalities in the plant operation or equipment malfunctions. It is supposed that by proper operator intervention after any alarm, the operation should get back to its normal range and no damage would occur.

“The processes and practices for determining, documenting, designing, operating, monitoring, and maintaining alarm systems” [1] are known as alarm management. As an overview, the alarm management lifecycle introduced in the ISA standard is shown in Figure 1.1. The stages of this lifecycle are explained briefly in the following.

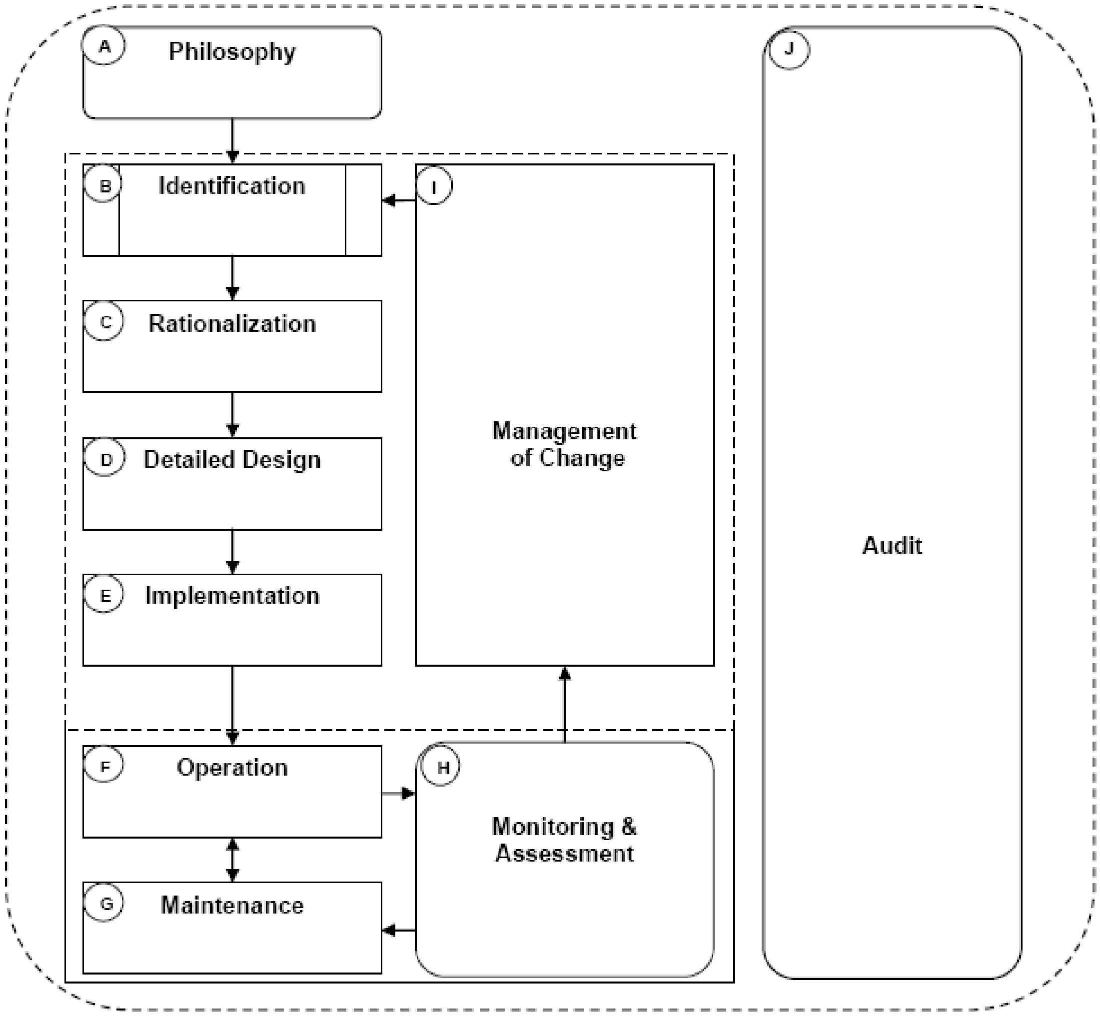


Figure 1.1: Alarm management lifecycle introduced in [1]

An alarm philosophy determines the objective of the alarm system and the process to achieve those objectives. It defines the basic principles of the alarm system and the processes to be used in each of the other alarm management lifecycle stages. For example, the definition of the alarm priority and the requirements for change in the alarm system are determined in the philosophy document. The philosophy document is prepared before designing of the alarm system to specify its requirements and the system that meets the requirements.

In the identification stage the necessary alarms are identified by using different methods such as process hazards analysis, safety requirements specifications, recommendations from an incident investigation and other possible approaches. So, in this stage the potential alarms are determined and the next step is to rationalize the alarms.

In the alarm rationalization stage the properties of every alarm is determined and documented. For example the priority of the alarm, its consequence and the action that should be taken by the operator.

The detailed design stage includes the design of alarm parameters and the advanced alarming techniques such as state based alarming and dynamic prioritization. This stage also includes the design of the annunciation of the alarm.

In the implementation stage the designed alarms are physically or logically installed in the system and their functionality is being tested. This stage also includes the operator training.

In the operation stage, the alarm system is active and operates normally.

In the maintenance stage, the alarm system is inactive while its functionality is being tested. The maintenance stage must be performed periodically to keep the alarm system within the requirements.

In the monitoring and assessment stage, the performance of the alarm system along with the individual alarms is monitored to check their accordance to the alarm philosophy.

In the management of change stage, the necessary changes to the alarm system according to the alarm philosophy are proposed and approved.

In the audit stage, some reviews on the performance of the alarm system are conducted to identify possible improvements which are not identified in the monitoring stage. These improvements may even include modifications to the alarm philosophy.

Establishment of a new alarm system starts from documenting of the alarm philosophy. For existing alarm systems, the monitoring or audit stages are the entry points to the alarm system lifecycle. All the stages of the lifecycle are necessary for maintaining the efficiency of the alarm system.

Before the advent of the distributed control systems (DCS), there were small number of well designed alarms that could give enough and accurate information about the plant situation to the operator. With the DCS, implementing alarms became quite easy and inexpensive. Since there was no limit for configuring alarms, the number of alarms in every industrial plant increased excessively. Following the huge number of alarms, the time consumption of the alarm design practice increased. So, the design of alarms was mostly performed poorly.

Poor alarm design results in receiving a lot of nuisance ("an alarm that annunciates excessively, unnecessarily, or does not return to normal after the correct response is taken" [1]) and redundant alarms during abnormalities in the plant operation. As many of the process variables are dependent to each other, one abnormality usually causes several alarms. Alarms that are caused due to the same problem are called redundant alarms.

Another problem in monitoring is receiving alarms while the operation is in its normal range. These alarms are called false alarms and are usually due to the noise or poor design of the alarm parameters.

All of these nuisance, redundant and false alarms result in alarm floods during some abnormalities in the plant operation. An alarm flood happens when the operator receives more alarms than he/she can respond to. So, it is hard to identify the most important alarms and the root problem. The average number of annunciated alarms per one operator is mentioned in the ISA standard [1] as is shown in Table 1.1.

Table 1.1: Average alarm rates [1]

Very Likely to be Acceptable	Maximum Manageable
150 Alarms per day	300 Alarms per day
6 Alarms per hour (average)	12 Alarms per hour (average)
1 Alarm per 10 minutes (average)	2 Alarms per 10 minutes (average)

Alarms appear on the operator console as massages including the tag names, time stamp, alarm identifier, some description about the alarm, its priority, plant name and maybe some other information. Every unique alarm is identified by its tag name, time stamp and its alarm identifier.

The time stamp may have different precisions according to the system. An alarm identifier is shown as PVHI, PNLO or similar abbreviations. PVHI means that the process variable has exceeded the upper limit of its normal range. PVLO annunciates that the process variable has hit its lower limit. In some cases there are two high and two low limits in the system. The first high or low limits show that the variable is out of its normal or optimum range, but, the second high or low limits show that the variable is in a more dangerous range.

Regardless of the type of the variable or the type of the alarm, the decision of raising an alarm is usually based on one criterion, which is the alarm limit or threshold. Since this is the simplest method of fault detection, some other techniques should be used to prevent alarm from chattering or other problems. Some of these techniques are alarm deadbands, delay timers and filters. Following is a survey of the research done in the alarm management area.

1.2 literature review

1.2.1 General research regarding alarm management

In this section the papers that discuss alarm management problems from a general point of view are discussed.

Bergquist et. al. [2] presented a computerized tool for alarm system improvement. The tool is an off-line approach that is applicable to any kind of plants. Proposed methods to eliminate nuisance alarms are as follow:

1- Creating a model of the system or part of it
2- Prioritizing and grouping the alarms
3- Shelving the repeating alarms
4- Tuning the alarm limits and delays

The tool uses signal processing methods and predictive algorithms. It helps with tuning of alarm limits and suggests alarm reduction algorithms to apply to the process signals. Available functions in the ACT (Alarm Clean up Toolbox) are:

1- Filters: IIR filters, averaging filter, median filter
2- Time delay
3- Difference function: It calculates the differences between successive process variable's values. If the difference is negative, which means the variable is decreasing, the alarm can be cleared.
4- Deadband
5- Alarm window function: It is a combination of time delay and difference function. The alarm stays off for a limited time while the process variable has exceeded the alarm threshold, but is bounded to a maximum value.

There is a function called LARA (Logical Alarm Reduction Algorithm) which categorizes the process signals into 14 different classes using past data and applying a rule based expert system. Then, it suggests the best processing technique for the signal based on its model.

Kyriakides et. al. [3] introduced a concept of an alarm processing algorithm performing the following tasks:

- Prioritization on the basis of area responsibility
- Root cause identification of alarms
- Elimination of multiple alarms from the same cause
- Prioritization on the basis of a predetermined list of alarm weights of importance
- Prioritization on the basis of recency
- Identification and recommendation of control actions
- Decision making assistance
- Actuation of controls

The algorithm is supposed to be automatic and able to interfere in the control system.

Larsson [4] presented an ongoing project on alarm sanitation. The goal is to automatically detect badly tuned alarms and report them to the operator along with some characteristics of corresponding process variables. Bad alarms are the ones with too wide or too narrow alarm thresholds. The proposed algorithm is supposed to perform the following tasks:

- Monitoring the behavior of alarms.
- Detect alarms that are activated several times during a time period and are being reset or ignored by the operator. Store their information in the database.
- Detect silent alarms, which are alarms that are never activated. Store their information in the database.

- Store some characteristics of the process variables that are monitored by bad alarms mentioned in above.
- Present the stored information to the operators at regular time intervals.

Izadi et. al. [5] have briefly discussed multivariate process monitoring, model based performance monitoring, threshold design and alarm variable processing techniques as methods for reduction of false and nuisance alarms.

Multivariate monitoring is the concept of monitoring a linear combination of some individual variables, which are called latent variables, instead of monitoring all of them individually. This idea is based on the fact that most of the process variables are correlated and monitoring all the variables separately results in having a lot of nuisance alarms. Model based monitoring is the concept of monitoring the process behavior instead of its individual variables. To use this method, availability of a precise model from the process is necessary.

Since process variables always carry some noise, occurrences of some false and missed alarms are inevitable. By performing some processing on the alarm variable, the rates of false and missed alarms can be reduced. Filtering, time delay and deadband are common techniques for this purpose.

Chowdgury et. al. [6] proposed a technique for reduction of the false alarm rate in fault detection. The technique is based on noise elimination of the residual signal. The residual signal is obtained by comparing the process measurement with its predicted value by a model.

During normal operation of the process, the residual signal will be a stochastic signal with known statistical characteristics and during the abnormal operation, the statistical characteristics of the signal changes. Since the residual signal contains noise, detection of abnormality will have some delay and probability of false and missed alarms are high.

It is proposed to model the residual signal as an AR structure. It is discussed that if the residual signal during the fault free operation is just a zero mean uncorrelated random signal, its modeling process gives a zero output. During the abnormal operation statistical characteristics of the residual signal changes, so, its AR model will not be zero anymore. Using this method eliminates the effect of noise on the fault detection.

Kondaveeti et. al. [7] presented two visualization tools to assess the performance of the alarm systems. The first tool is called “high density alarm plot”. The basic idea is to identify highly chattering tags by plotting a colored graph consisting of all tags during a specific period of time. The time interval is divided into 10 minute bins and the number of alarms for every tag during the bins is shown by an appropriate color.

Another tool which is known as an “alarm similarity color map” is also presented to identify the redundant alarms. The Jaccard similarity index is used to measure the similarity between the alarms. The similarity matrix is rearranged and the similarity between the alarms is shown by different colors corresponding to the strength of the similarity.

1.2.2 Research regarding the design of alarms

Following is a summary of the papers which analytically discuss specific problems regarding the design of alarm parameters.

Kondaveeti et. al. [8] discussed multivariate alarming. Since there are a lot of alarming variables in every industrial plant, many of the alarms are correlated to each other and arise for the same reason. This causes alarm floods and operator will be overwhelmed by the alarms during abnormalities. In this paper the advantages of multivariate alarming is discussed against the univariate alarming.

It can be shown that by multivariate monitoring, the number of false and missed alarms will decrease without the increase in abnormality detection. It is proposed to use the principal component analysis method to obtain the principal components. By using Q and T^2 tests, it is possible to detect abnormalities with more accuracy and receive fewer alarms.

Izadi et. al. [9] discussed the effect of applying filtering, time delay and deadband on the alarm variables and proposed a method for their optimal design. The method is an off-line approach based on the ROC curve. The ROC (Receiver Operating Characteristic) curve is mentioned as a plot of probability of missed alarms versus the probability of false alarms. The ideal point in the ROC curve is the origin which guarantees zero false and missed alarms. The techniques of filter, time delay and deadband design are used to make the ROC curve closer to the origin.

Filters are capable of changing the statistical distributions of the data. They can be used in cases that the normal and abnormal parts of the data have a strong overlap. Common filters in industry are moving average, exponentially weighted moving average (EWMA) and cumulative sum (CUSUM).

Another technique for reduction of false and missed alarm rates is time delay. A time delay can be considered in raising an alarm (on delay) or clearing the alarm (off delay). By increasing the time delay the accuracy of the alarm will increase and the ROC curve gets closer to the origin but, the abnormality detection will have some delay.

A method for designing filters, deadbands and time delays is proposed based on the ROC curve [9]. It is proposed that the ROC curve should be plotted for different design methods and parameters. If a limit on the probabilities of missed and false alarms is known, a technique and its corresponding design parameters should be chosen which satisfy the limits.

Adnan et. al. [10] studied the detection delay in industrial alarm systems due to alarm deadbands and delay timers. A detection delay is the time difference between the exact time of the actual fault occurrence and the time of the alarm. Markov processes are used to calculate the detection delays for a process data with known distribution. Supposed process data consists of one normal and one abnormal parts with known distribution models. The expected value of the detection delay with deadband in the system is obtained as:

$$E(DD) = \frac{p_1 q_1 + p_2 (1 - q_2)}{q_2 (p_1 + p_2)} \tag{1.1}$$

p_1, p_2, q_1 and q_2 are obtained from the probability distribution of the data. For the delay timers, the average of the detection delay is dependent to the number of on delay samples (n) and number of off delay samples (m) and is expressed as:

$$E(DD) = \frac{p_2^{m-1} \left(p_1^n q_1 \sum_{i=0}^{n-1} q_2^i + p_2 \left(\sum_{j=0}^{n-1} p_1^j \sum_{k=0}^{n-j-1} q_2^k - q_2^n \sum_{i=0}^{n-1} p_1^i \right) \right)}{q_2^n \left(p_2^m \sum_{i=0}^{n-1} p_1^i + p_1^n \sum_{i=0}^{m-1} p_2^i \right)} \tag{1.2}$$

The average value of the detection delay can be used in the design procedures to avoid unsafe time delays due to the deadband or delay timers.

There are some recommendations for deadband and time delay design in EEMUA [11] and ISA [1] standards. Table 1.2 shows these recommended deadbands based on the type of the process variables and Table 1.3 shows the recommended time delays.

Table 1.2: Standard's recommendations for alarm deadbands

Signal type	Deadband
Flow Rate	5%
Temperature	1%
Level	5%
Pressure	2%

Table 1.3: Standard's recommendations for delay time

Signal type	Delay Time (on or off)
Flow Rate	15 seconds
Temperature	60 seconds
Level	60 seconds
Pressure	15 seconds

Hugo [12] presented a method for designing measurement and time deadbands by applying time series analysis methods. Measurement deadband determines how much the process variable should pass the alarm threshold to clear the alarm. Time deadband determines the minimum time that should be between two successive alarms. It is proposed that every process variable can be modeled by an autoregressive-integrated-moving average (ARIMA) structure as:

$$y_t = \frac{\theta(z^{-1})}{\nabla^d \varphi(z^{-1})} a_t \tag{1.3}$$

y_t is the process measurement at time *t*, a_t is white noise with variance σ_a.

This model can be used to predict the future values of the process variable and its prediction interval. Measurement deadband should be redesigned in the time of occurrence of every alarm in a way that every change in the process measurement due to the noise falls within the deadband or mathematically $deadband \geq \hat{y}_{t+l} - C.I.$. *L* is the prediction horizon and $\hat{y}_{t+l}$ is the prediction of the process variable at time *t*+ *L* and *C.I.* is its confidence interval.

Since process variables are very likely to have different structures during different modes of operation, an identification routine should be running on-line.

For time deadband design again the predicted values by the model and corresponding prediction intervals are used. Time deadband, which is the minimum time that should pass before the alarm can reoccur, should be determined as the closest time in which the predicted process value plus its confidence interval is equal or greater than the alarm threshold.

Kondaveeti et. al. [13] studied the alarm chattering and proposed a quantitative definition for it based on run length distributions. Alarm chattering happens when an alarm repeatedly goes on and off in a short time interval. There is no standard definition for alarm chattering except for some general rules such as repetition of the alarm in a minute for more than two times.

Run length from the alarm management perspective is the time differences between successive alarms in seconds. For obtaining the run length of an alarm, a reasonably large amount of alarm data should be used to calculate the run lengths. The number of repetition of every run length during the total time interval is called alarm count. Run length distribution is obtained by plotting the alarm counts versus the run lengths. By dividing the alarm counts to their total number, a discrete probability distribution function for run lengths is obtained. The chattering index is defined as a weighted summation of the normalized alarm counts. Since the run lengths closer to 1 second cause the most chattering, the weighting function should be chosen in a way to attenuate the effect of further run lengths. The weighting function is chosen as the inverse of the run lengths. So the chattering is defined as:

$$\frac{\sum_{r} \frac{AC_r}{r}}{\sum_{r} AC_r} \tag{1.4}$$

AC is abbreviation of Alarm Counts and RL is abbreviation of Run Length. This chattering index gives a number between zero (no chattering) and one (as the maximum amount of chattering). Chattering index of one happens when the alarm repeats every second during the total time. If it is known that the alarms caused by one abnormality won't last for more than a specified time interval, then, the run lengths more than that interval can be ignored in calculation of chattering.

1.3 Motivation of this thesis

Alarm management has recently gained lots of attention from industries and also academia. Since it is almost a new research area, there are still unsolved problems regarding the design of the alarm parameters such as alarm limits and deadbands. So in the first part of this study, the relation between the alarm limit and alarm deadband with chattering and false and missed alarm rates is investigated.

The second part of this study is about the relation between chattering with alarm parameters and statistical characteristics of the data. Although chattering alarms are one of the important problems of alarm systems, there is not yet any analytical design method considering reduction of chattering. So, part of this study is about finding the analytical relation between chattering with alarm parameters and statistical characteristics of the process data.

1.4 Outline of the thesis

In the second chapter the effect of alarm deadbands and alarm limits on chattering and false and missed alarm rates is investigated. Two equations are proposed to estimate the optimal alarm limit with respect to deadband and statistical characteristics of the data.

In the third chapter, the chattering index is analytically derived as a mathematical function of alarm parameters and statistical characteristics of the data. Chapter 4 contains two examples of applying the proposed methods in chapters 2 and 3 in the design of alarm parameters considering two industrial tags. The last chapter is conclusion and future work.

2 Deriving optimal alarm limits and deadbands

2.1 Introduction

The alarm deadband is a widely used technique in industrial alarm systems to reduce the alarm chattering. It is implemented in modern DCS (distributed control systems). Therefore, implementing an alarm deadband does not need any hardware or special software application. This is the reason that deadbands are quite popular in alarm configurations. In the following the concept of designing deadbands is discussed.

In practice most of the process measurements are corrupted by noise from different sources. A noise can cause the alarm to repeatedly go on and off while the signal is close to the threshold. Alarm deadband prevents the alarm from clearing due to the noise on the process measurement. It determines a second limit for clearing the alarm to make sure that the alarm goes off because of a change in the signal structure not the noise.

A deadband is represented as a percentage that should be multiplied to the range of the alarm variable or the alarm limit to get the deadband width. Since the range of the variable is usually unknown, deadband is represented as a percentage of the alarm limit in this work. So the deadband width is obtained by multiplying the deadband to the alarm limit.

For the case of high alarms, the deadband limit is always less than the alarm limit and is obtained as $L(1-DB)$; L is the alarm limit and DB is the deadband. The alarm goes on when the process signal exceeds the alarm threshold and it clears when the signal is less than the deadband limit. For example, consider Figure 2.1.

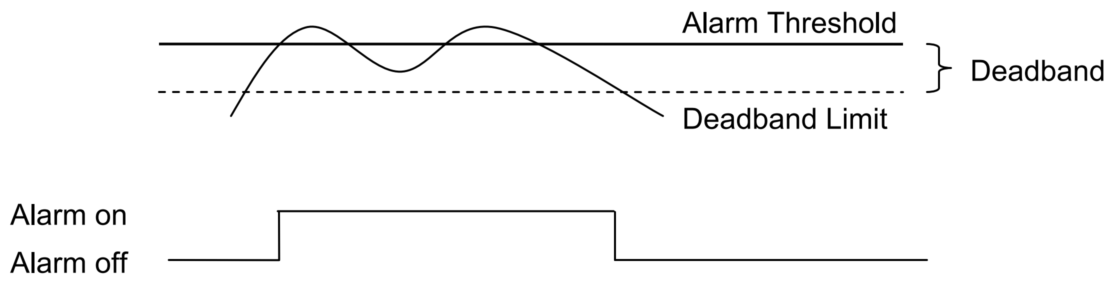


Figure 2.1: An example of a high alarm with deadband

For the supposed process signal in Figure 2.1, the alarm annunciates when the signal goes beyond the alarm threshold, but it doesn't clear when the signal is changing within the deadband. So, if the exact measurement of the signal is higher than the alarm threshold and the amplitude of the noise is less than the deadband width, the alarm will stay on even if the measurement is lower than the threshold. This will reduce the number of repetition of the alarm due to one abnormality.

For low alarm cases, the deadband limit is higher than the alarm limit and is obtained as $L(1+db)$. An example is shown in Figure 2.2. The alarm goes on when the process signal goes lower than the alarm threshold and clears when it is higher than the deadband limit.

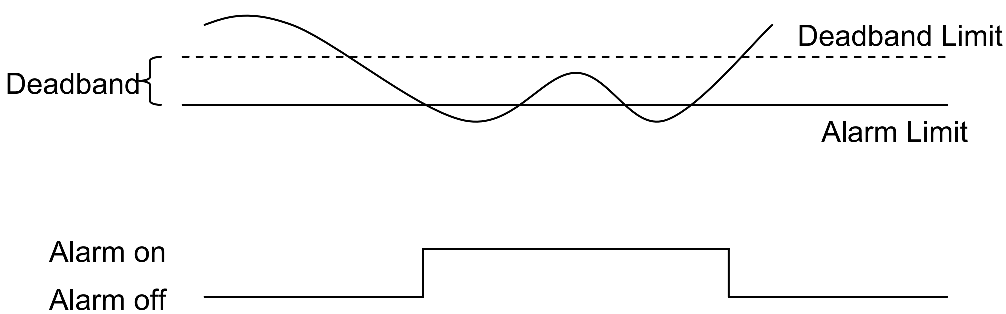


Figure 2.2: An example of a low alarm with deadband

As was mentioned in Chapter 1, there are some general guidelines in standards for designing deadbands. Since every process variable has a different structure and is imposed to different noises, following one rule for deadband design doesn't always generate the best result. It is necessary to consider the history of every process variable in its special deadband design.

In the design of alarm parameters, reduction of false and missed alarm rates are also important factors besides the chattering reduction. In the following section the method of calculation of false and missed alarm rates in the presence of deadband is explained.

2.2 Calculation of false and missed alarm rates

In the study of alarm deadbands, the part of the data during the transition from normal range to abnormal range is important. Also, at least one part of the data should be close to the threshold to cause chattering. So, the simulated data sets that are used hereafter all include two parts; one normal and one abnormal. For example Figure 2.3 plots the probability distribution functions of the two parts of some simulated data. It is assumed that the data has Gaussian distribution in both parts

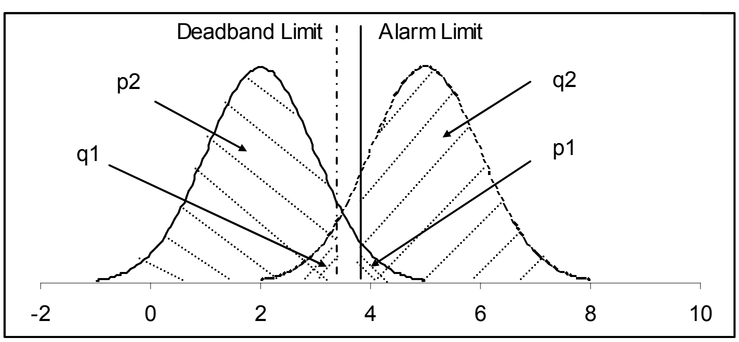


Figure 2.3: PDF of normal and abnormal parts of simulated data

The solid curve is the PDF of the data in its normal range and the dashed curve is the PDF of the abnormal part of the data. Alarm and deadband limits are shown in the figure. p_1, p_2, q_1 and q_2 are mathematically written as the following formulas:

$$p_1 = 0.5 - 0.5 erf(\frac{L - \mu_n}{\sqrt{2}\sigma_n}) \qquad p_2 = 0.5 + 0.5 erf(\frac{L(1-db) - \mu_n}{\sqrt{2}\sigma_n}) \tag{2.1}$$

$$q_1 = 0.5 + 0.5 erf(\frac{L(1-db) - \mu_a}{\sqrt{2}\sigma_a}) \qquad q_2 = 0.5 - 0.5 erf(\frac{L - \mu_a}{\sqrt{2}\sigma_a}) \tag{2.2}$$

μ_n and σ_n are the average and standard deviation of the normal part of the data. μ_a and σ_a are the average and standard deviation of the abnormal part of the data. L is the alarm limit and db is alarm deadband. *erf*(.) represents the error function with the following formula:

$$erf(x) = \frac{2}{\sqrt{\pi}} \int_0^x e^{-t^2}\, dt$$

A method for calculation of false and missed alarm rates is discussed in [9]. The basic assumption is that the distribution of the process data is known. Markov chain method is used to calculate P_{fa} and P_{ma}. Figure 2.4 depicts a Markov process for the normal part of the data.

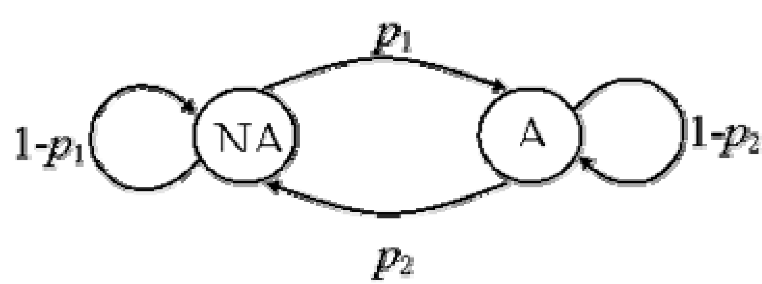


Figure 2.4: Markov diagram of an alarm with deadband

Assuming that the process variable is firstly in its normal range, the alarm is in the no alarm state (NA). If the next sample is again in the normal range with probability of 1-p_1, there will still be no alarm. The alarm is raised when the sample exceeds the alarm threshold by probability of p_1. The alarm state only transits to off state when the consecutive sample is lower than the deadband limit. So, the alarm stays on with the probability of 1-p_2 and clears with probability of p_2.

The single step probability transition matrix is

$$\begin{array}{ccc} & NA & A \\ P = & \left[\begin{array}{c} 1-P_1 \\ P_2 \end{array}\right. & \left.\begin{array}{c} P_1 \\ 1-P_2 \end{array}\right] \end{array}.$$

For the case of the alarm deadband, the steady state probability vector is calculated as

$$\begin{array}{ccc} & NA & A \\ \pi = & \left[\dfrac{p_2}{p_1+p_2}\right. & \left.\dfrac{p_1}{p_1+p_2}\right] \end{array}.$$

So, the probability of false alarm is:

$$p_{fa} = \frac{p_1}{p_1+p_2} \tag{2.3}$$

The probability of missed alarm can be obtained in the same way by considering the PDF of the abnormal part of the data. The steady state probability vector for abnormal part of the data will be obtained as $\begin{array}{cc} NA & A \\ \left[\dfrac{q_1}{q_1+q_2}\right. & \left.\dfrac{q_2}{q_1+q_2}\right] \end{array}$. So the probability of missed alarm is:

$$p_{ma} = \frac{q_1}{q_1+q_2} \tag{2.4}$$

This method of calculation of P_{fa} and P_{ma} can be used considering any kind of PDFs.

2.3 Definition of optimal deadband and optimal alarm threshold

As was mentioned, the purpose of the alarm deadband is mainly reduction of the alarm chattering. As there is a quantitative definition for chattering [13], optimal alarm parameters can be defined as the parameters that generate the least chattering.

There are two procedures to obtain the optimal alarm parameters by this definition. One is to perform simulations on the process data for different alarm parameters and choose parameters that correspond to the least chattering. The precision of this procedure depends on the selection of the range of the parameters and the step size of their changes. Using this procedure can be quite time consuming, especially if the design of more than one alarm parameter is considered. For example, if the goal is designing both alarm threshold and deadband, it is necessary to firstly consider a reasonable range for alarm threshold. Choosing a small step size for the threshold, the threshold should move from its least value to the maximum value. For every threshold, deadband should be changing from zero to its maximum possible value with a reasonable small step size. For every threshold and deadband, the chattering has to be calculated in a separate simulation run. Then the parameters that satisfy a limit on the chattering should be chosen. So, there will be lots of simulations that don’t guarantee a precise design and take a lot of time and processing power.

The other method for obtaining the optimal parameters is to use the mathematical expression of chattering that is proposed in the next chapter. Chattering is derived as a mathematical function of the statistical characteristics of the process data and alarm parameters. By calculating the statistical characteristics of the process variable from its history, chattering can be obtained as a function of alarm parameters. So, it is possible to get the optimal values by minimizing the mathematical function without any simulation.

As was mentioned before, another goal in the alarm design is reduction of false and missed alarm rates. False alarms distract the operator and missed alarms leave the operator unaware of abnormality in the plant operation. So, the optimal alarm parameters can be defined as the values that minimize the following objective function $C_1P_{ma}^2+C_2P_{fa}^2$.

C_1 and C_2 are the parameters of the objective function and can be chosen according to the situation.

If C_1 and C_2 have the same values, false and missed alarm rates are considered to be of equal importance. In this case the optimal alarm parameters would be the same as the values that minimize the distance of the ROC curve from the origin. As was mentioned in Chapter 1, ROC curves are the plots of missed alarm versus false alarm rates for different thresholds. So the distance of each point in the ROC curve from the origin is $P_{ma}^2+P_{fa}^2$. False and missed alarm rates are zero at the origin. So, the origin is the ideal point in a ROC curve.

Any point in the ROC curve can be obtained as the optimal point by choosing different values for parameters C_1 and C_2. These two coefficients are not fixed and their selection depends on the opinion of alarm engineers.

In this work, C_1 and C_2 are considered the same. The advantage of this choice is that the optimal parameters based on this objective function will usually be very close to the optimal parameters based on the chattering. So, it is possible to minimize both false and missed alarm rates simultaneously with minimization of the chattering.

To see the reason for closeness of optimal parameters based on chattering with optimal parameters based on the least distance from the ROC curve, it is useful to observe how chattering is related to distribution of the data and alarm threshold.

For example, a simulated data with Gaussian distribution, which is depicted in Figure 2.5, is considered. In Figure 2.6 the probability distribution function of the data is plotted in solid curve. Two simulations are performed on the data. In each simulation, the threshold varies from 0 to 5. Deadband is 0% in the first simulation and 15% in the second one. For each threshold, chattering and probability of false alarms are obtained in the two simulations.

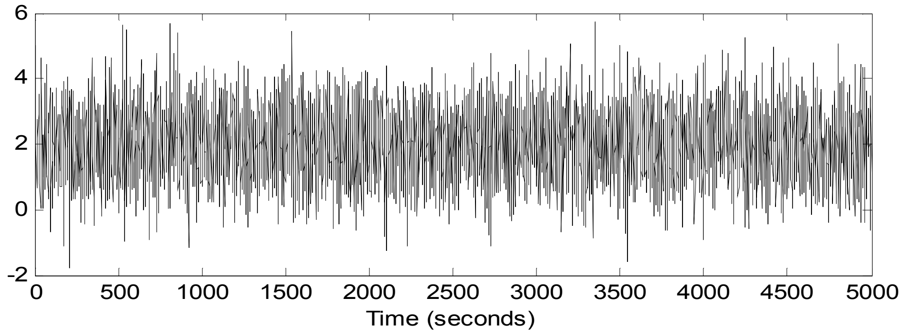


Figure 2.5: Simulated process data

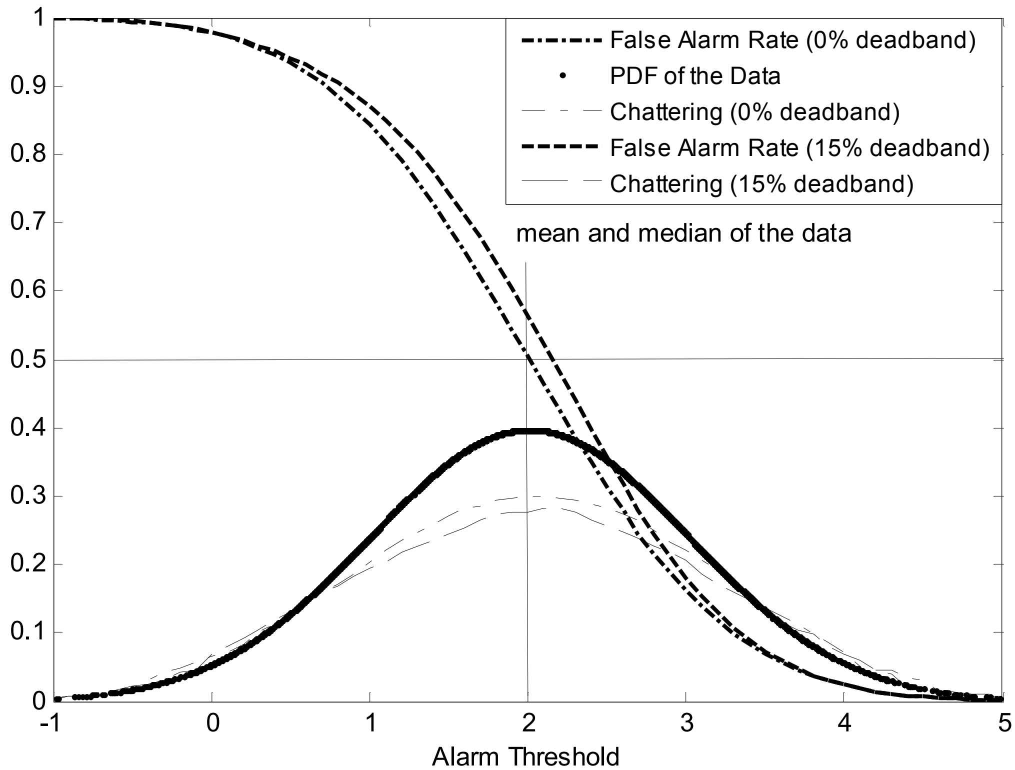


Figure 2.6: PDF, chattering and false alarm rate for the simulated data in Figure 2.5

Probability of false alarm for zero deadband is depicted in the thicker dash dot line in Figure 2.6. Probability of false alarm equals to 0.5 when the threshold is on 2, which is the mean and median value of the data. The curve of false alarm rate for 15% deadband is depicted in the thicker dash line in Figure 2.6. The false alarm rate with 0.15% deadband hits 0.5 when the threshold is on 2.16.

As it is expected, false alarm rate increases with increasing the deadband. As was shown, the false alarm rate is obtained as $\frac{P_1}{P_1+P_2}$. By increasing the deadband, P_1 doesn't change while P_2 decreases. So the false alarm rate increases.

Chattering is obtained in the simulations for every deadband and threshold. As can be seen in Figure 2.6, the chattering curve for zero deadband has the same shape of the PDF of the data. The maximum chattering happens when the threshold is on 2, which corresponds to the false alarm rate of 0.5. Chattering is also symmetric around its maximum value.

The behaviour of chattering with respect to the threshold is understandable by studying the root cause of chattering. As was mentioned, chattering happens by repeated transitions of the alarm state from on to off. So the probability of clearing the alarm is as important as the probability of triggering the alarm in causing chattering.

The probability of alarming was obtained as $\frac{P_1}{P_1+P_2}$ and the probability of clearing the alarm is $\frac{P_2}{P_1+P_2}$. So, for example if the threshold is in the left half of the distribution of the data, probability of the alarm state to be on is more than the probability of the alarm state to be off. It means that the probability of transition of the alarm from on state to off is smaller compared to the case that both probabilities are equal. Since only the transition of the alarm state is important in causing chattering, the chattering would be smaller in this case.

The same discussion is true when the threshold is on the right half of the distribution of the data. In this case the probability of alarming would be less than the probability of clearing the alarm. So, the probability of transition of the alarm would be smaller compared to the case that the probability of alarming is equal to the probability of no alarm.

From these discussions it can be seen that the probabilities of alarming and clearing the alarm have the same contribution in causing chattering. So, the maximum value of chattering happens when the probability of false alarm equals to 0.5. It is always true when considering different distribution types. The maximum number of alarms and chattering, always happen on a threshold that has the same probability of alarming and clearing the alarm.

In the case of zero deadband, the false alarm rate curve is symmetric around 0.5. Thus, movement of the threshold from the mean value of the distribution to the right hand side reduces the probability of alarming in the same way that it reduces the probability of clearing the alarm if it was moved toward the left half of the distribution. This is the reason why chattering has its maximum value on the mean of the symmetric distribution of the data and is symmetric about that point.

As was discussed, by increasing the deadband from zero the probability of false alarm increases while the probability of clearing the alarm decreases. So, the chattering is lower than the chattering in the case of zero deadband, as is seen in Figure 2.6. The other effect of deadband is that the threshold, in which the probability of alarm equals to the probability of no alarm, moves to the right hand side of the PDF of the data.

It is possible to calculate the threshold corresponding to equal probabilities of alarm and no alarm states. We need to find the threshold where P_1=P_2. It happens when the deadband line and the threshold are symmetric around the median value of the distribution, which is 2 in this example. The following procedure can be used in calculation of that specific threshold:

$$m - L(1-db) = L - m$$

$$L = \frac{2m}{2-db} \quad (2.5)$$

where m is the median of the distribution.

For the data in Figure 2.6 with 15% deadband, the threshold is calculated as 2.16, which corresponds to the threshold obtained in the simulation.

For the case that the data is in the abnormal range, the same discussion can be made. The chattering has its highest value when the probability of missed alarm equals to the probability of alarming and decreases by moving the threshold to the right or left hand side of the PDF of the abnormal part of the data. So, the chattering curve has the same trend as the P_{ma} carve for the thresholds less than the threshold corresponding to the highest chattering (considering high alarm).

Since in the design of deadbands, the data should include one normal and one abnormal part, it is good to see how the chattering of combination of the two parts varies with the alarm limit. In Figure 2.7 probability distribution functions of a simulated data with a normal and an abnormal part are depicted. The solid PDF corresponds to the part of the data that is assumed to be in the normal range and the dotted PDF corresponds to the abnormal data.

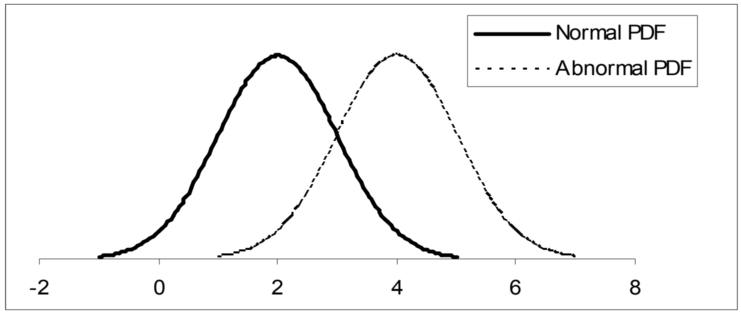


Figure 2.7: PDF of normal and abnormal parts of a simulated data

Figure 2.8 depicts the chattering of each part of the data separately along with false and missed alarm rates. The chattering of the total data is plotted in thin solid line and $(P_{ma}^2+P_{fa}^2)^{0.5}$ is depicted in thicker solid line.

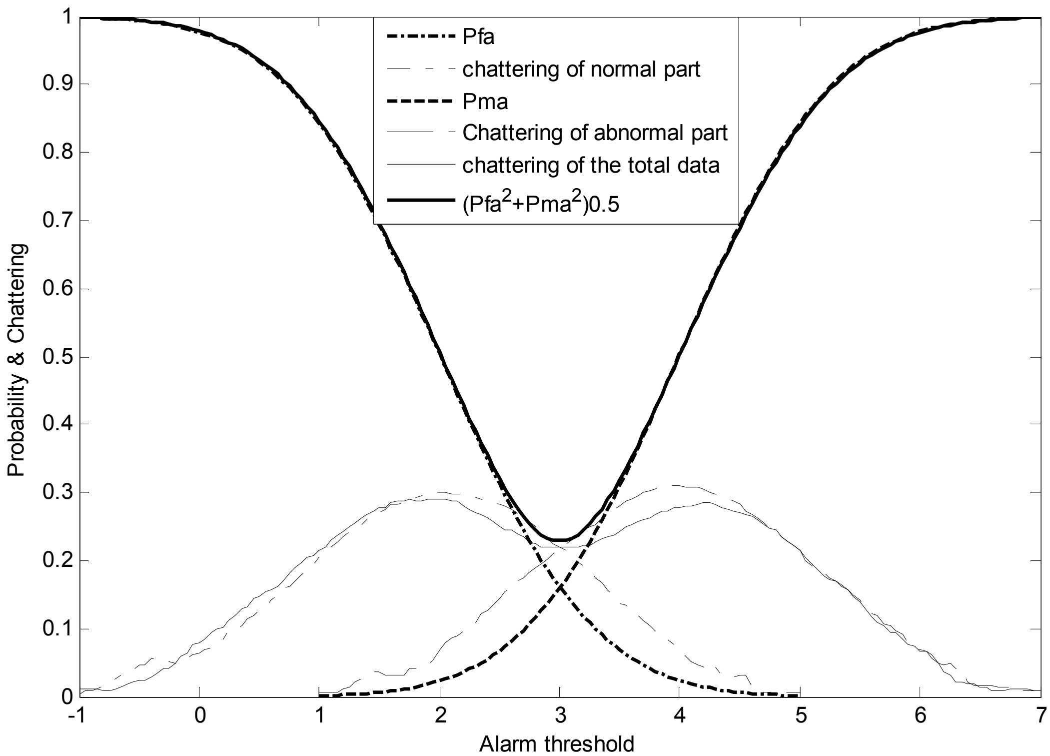


Figure 2.8: Chattering and false and missed alarm rates for the simulated data in Figure 2.7 with no deadband

From Figure 2.8 it can be seen that the minimum of the chattering happens at the same threshold as the minimum of summation of false and missed alarm rates happens. This is because for each part of the data the behaviour of chattering curve and the false or missed alarm rates are the same when the threshold is between the mean values of normal and abnormal parts of the data. The same simulations are performed considering the same data but with considering 20% deadband.

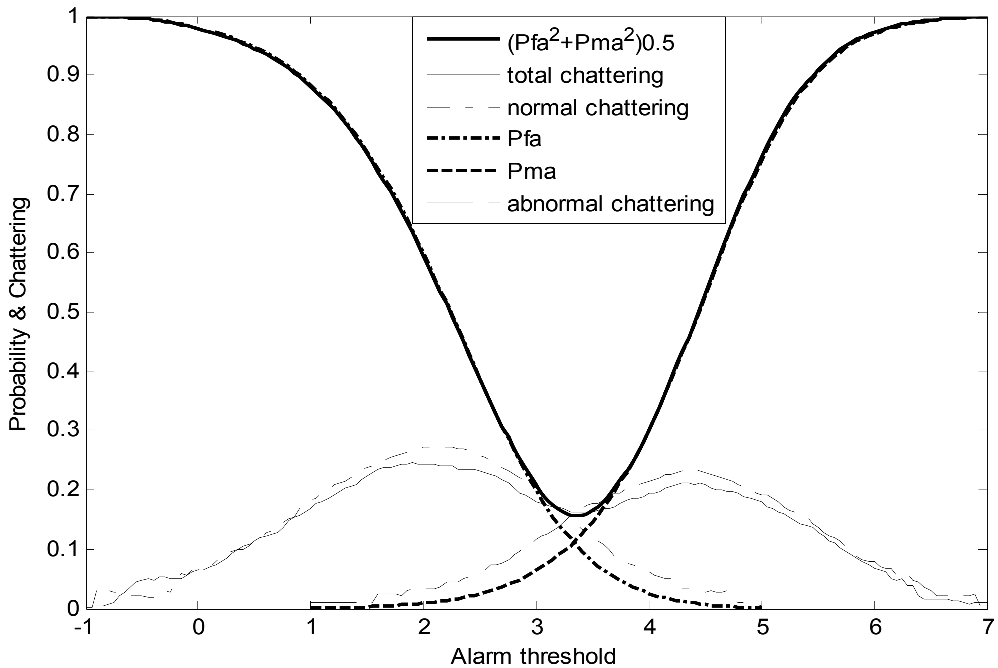


Figure 2.9: Chattering, false and missed alarm rates of the simulated data in Figure 2.7 with 20% deadband

In Figure 2.9 it can be seen that the threshold corresponding to the minimum chattering is equal to the threshold corresponding to the minimum summation of squared false and missed alarm rates.

Now the behaviour of chattering and probability of alarming in the case of non symmetric distributions is considered. In Figure 2.10, the PDF of some simulated data that has chi-squared distribution with 6 degrees of freedom is plotted in dots. Chattering is calculated in the simulation for alarm limits between zero and 25 and is plotted in Figure 2.10 in the dashed line. Also the probability of false alarm is depicted in the dash dot line.

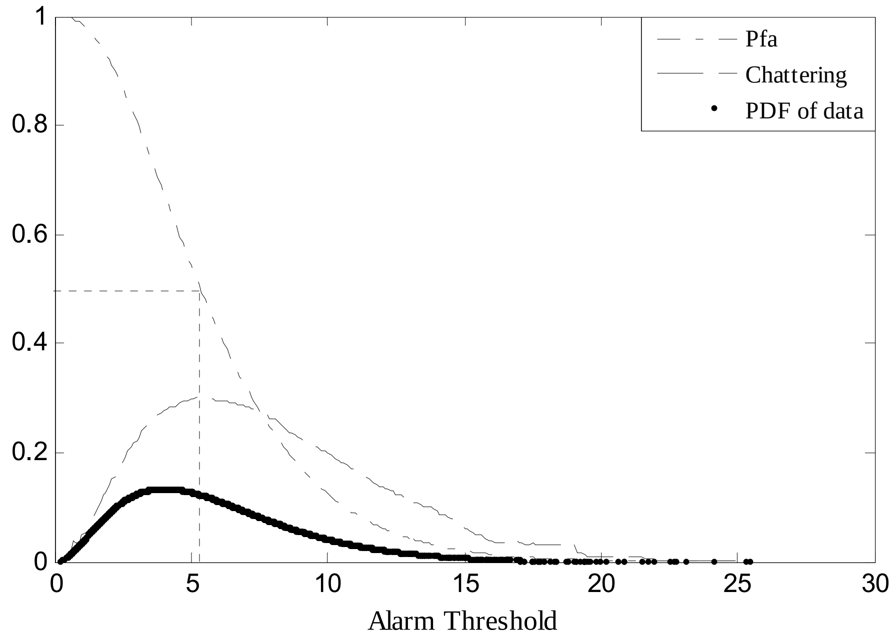


Figure 2.10: PDF and chattering and false alarm rate of a simulated data

The maximum chattering happens when the threshold is on 5.3, which is the threshold where probability of alarming equals to the probability of no alarm. The chattering decreases for the thresholds greater than 5.3 like the P_{fa} curve. Equation 2.5 can be used to find the threshold corresponding to the maximum chattering.

It was shown that the chattering has its maximum value when the probability of alarming is 0.5 and the corresponding threshold can be calculated for every kind of data distributions. So, it can be said that if the range of the threshold is between the thresholds corresponding to the maximum chattering of the normal and abnormal parts of the data, then the optimal parameters based on chattering always correspond to the optimal parameters corresponding to the least summation of false and missed alarm rates.

2.4 Effect of deadbands on false and missed alarm rates considering high alarm

In this session effectiveness of the deadband is investigated by performing several simulations. First, the trade-off between false and missed alarm rates in the deadband design is explained in another way.

For example, a simulated process data is depicted in Figure 2.11. The data includes two parts. The first half represents the data in its normal range and the second half is in the abnormal range of the data. The PDFs of its normal and abnormal parts are Gaussian. The mean value of the normal part is 2 with the standard deviation of 1 and the abnormal part has the mean value of 5 and standard deviation of 1.

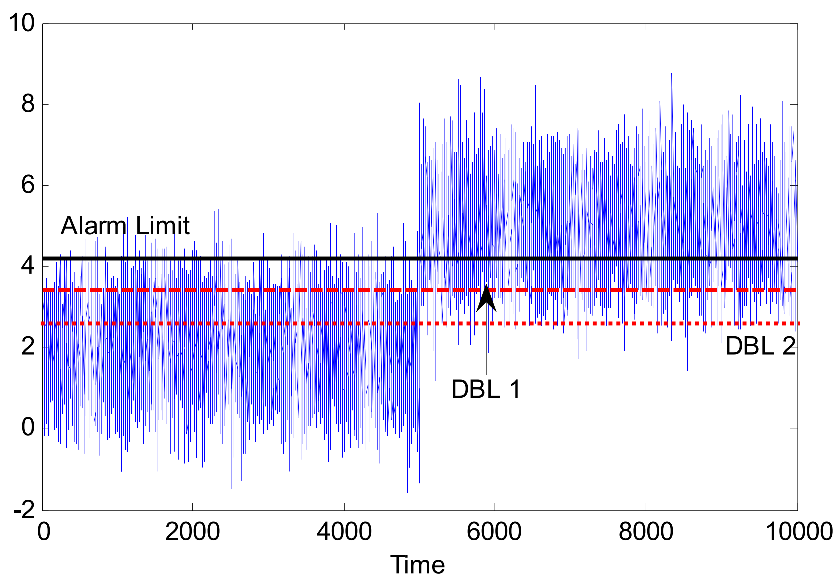


Figure 2.11: Simulated data

Consider a nominal alarm threshold as is depicted in Figure 2.11 and two different deadband limits (DBL). Deadband limit 1 is closer to the alarm threshold and corresponds to smaller deadband compared to deadband limit 2.

Considering the abnormal part of the data (second half) the numbers of data samples that are lower than the deadband limit are greater by considering deadband limit 1 compared to deadband limit 2. It means that number of clearing the alarm and repeating it would be lower by considering deadband limit 2. So, the abnormal part of the data will generate lower alarm chatter by increasing the deadband. Also the number of missed alarms will be less.

Considering the normal part of the data (first half), the number of samples beneath the deadband limit 1 is lower than the number of samples beneath the deadband limit 2. It means that the alarm would stay in the on state for longer duration when the deadband is larger. This implies more false alarms and chattering. So there is a trade-off between false and missed alarm rates in the design of deadbands.

Considering the data in Figure 2.11 a simulation is performed in which the summation of squared false and missed alarm rates ($(P_{ma}^2+P_{fa}^2)^{0.5}$) is calculated for three different alarm thresholds and deadbands ranging from 0 to 0.4. The results are shown in Figure 2.12.

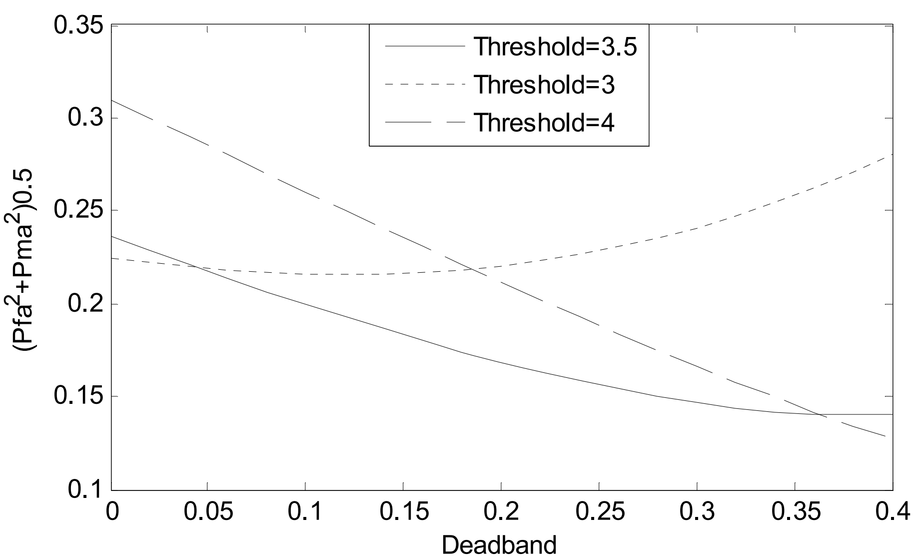


Figure 2.12: $(P_{ma}^2+P_{fa}^2)^{0.5}$ for different thresholds and deadbands for data in Figure 2.11

In Figure 2.12 three different behaviours are seen. The solid line corresponds to the alarm threshold on the average of the median values of normal and abnormal parts of the data. For this threshold the summation of missed and false alarm rates decreases by increasing the deadband till the value of 0.1 and then increases for higher deadbands. This is due to the fact that increasing the deadband increases the probability of false alarm while it reduces the probability of missed alarms.

The behaviour of the summation of the false and missed alarm rates is very sensitive to the alarm threshold. In the case that the alarm threshold is less than the average of median values of normal and abnormal parts of the data, usually increasing the deadband increases the sum of squared missed and false alarm rates. Because the alarm threshold is closer to the normal part, the increase in the false alarm rate is expected to be more than the decrease in the missed alarm rate.

For the case that the alarm threshold is on 4, the increase in the deadband value is more effective on reducing the missed alarm rate compared to increasing the false alarm rate. So as is seen in Figure 2.12 the sum of missed and false alarm rates decreases with increasing the deadband.

Another simulation is performed on the data in Figure 2.11. In this simulation the summation of squared false and missed alarm rates is calculated for 6 different deadbands and thresholds moving from 1 to 5. The result is shown in Figure 2.13.

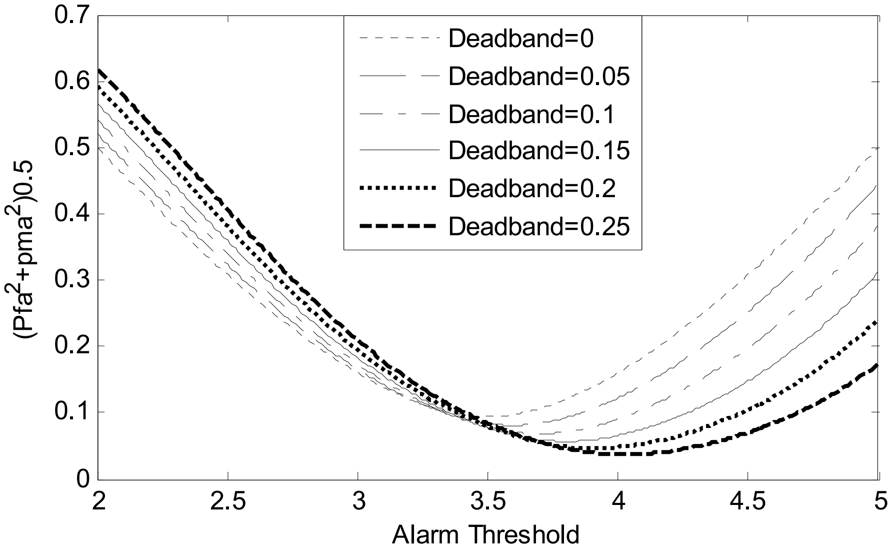


Figure 2.13: $(P_{ma}{}^2+P_{fa}{}^2)^{0.5}$ for different deadbands and thresholds for data in Figure 2.11

From Figure 2.13 it is seen that for each deadband, the summation decreases from its maximum value to its minimum value and again increases. While the alarm limit is less than 3.5 (average of mean values of normal and abnormal part of the data) the curves corresponding to higher deadbands have higher amounts of the summation. For the thresholds greater than 3.5 the curves with higher deadbands are in lower positions.

The other important feature of Figure 2.13 is that the alarm limit corresponding to the minimum of the summation of false and missed alarm rates moves toward the abnormal part of the data for higher deadbands. For zero deadband the optimal limit is on 3.5 while for 25% deadband it is about 4.

From Figures 2.13 and 2.12 it can be seen that for a fixed alarm limit, increasing the deadband more than some saturation value can't reduce the summation of false and missed alarm rates and even it might result in higher values of the summation. The same simulation is performed considering the chattering instead of the summation. The result is depicted in Figure 2.14.

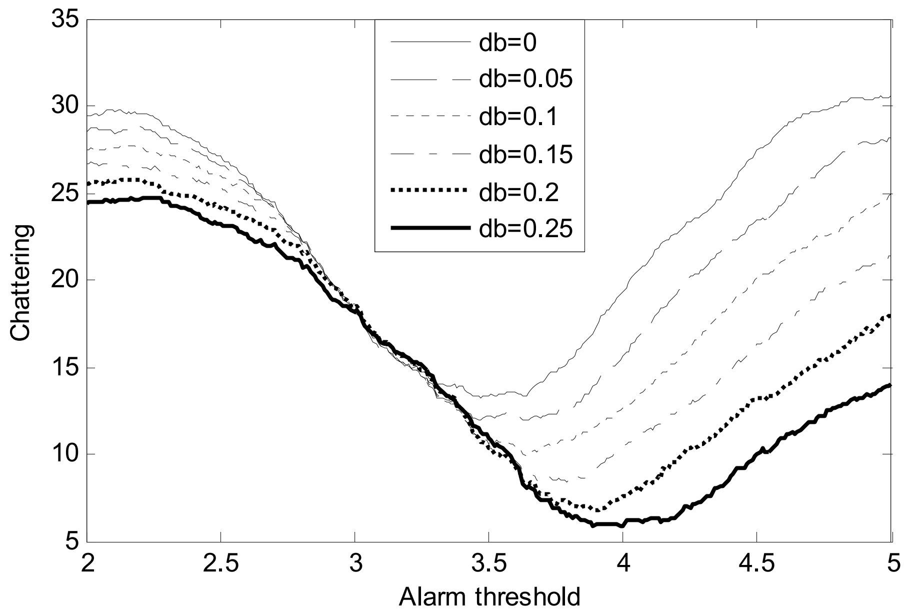


Figure 2.14: Chattering of the data in Figure 2.11

In Figure 2.14 the same features as in Figure 2.13 are observed. Since chattering is calculated based on one set of numbers that are randomly generated from the distribution of the data, there is some randomness in chattering indexes which results in unsmooth chattering curves.

To investigate the effect of the statistical characteristics of the data on the shape of the chattering and summation curves, the same simulations are performed on another data set. Figure 2.15 depicts the data. The data has standard deviation of 2 in the abnormal part and the other characteristics are the same as the data in Figure 2.11.

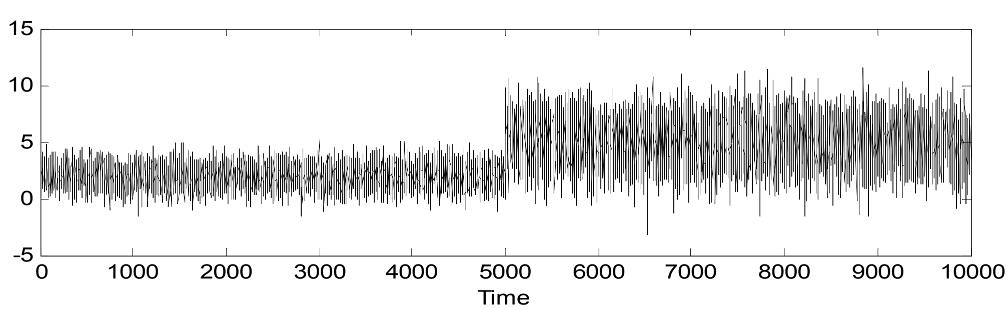


Figure 2.15: Simulated data

Figure 2.16 depicts the summation for different deadbands and same thresholds as in Figure 2.12.

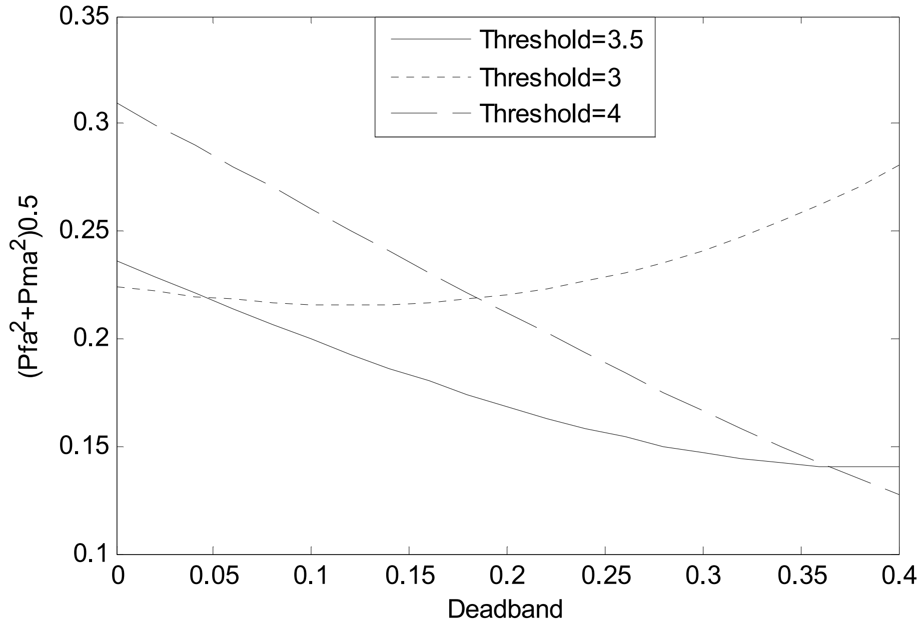


Figure 2.16: $(P_{ma}^2+P_{fa}^2)^{0.5}$ for different thresholds and deadbands for data in Figure 2.15

Since the standard deviation of the abnormal part of the data is larger compared to the data in Figure 2.11, the shape of the curves are different in this figure. For the thresholds of 3.5 and 4 the curves keep decreasing. For the threshold of 3, the curve decreases a little bit until the deadband equals to 0.1 and then increases, like the threshold of 3.5 in the Figure 2.12.

Figure 2.17 depicts the summation of squared false and missed alarm rates considering 6 different deadbands and thresholds from 2 to 5 for the data in Figure 2.15. In Figure 2.17 compared to Figure 2.13 the optimal thresholds are closer to the normal part of the data. The optimal threshold for zero deadband is close to 3 and the optimal threshold for 25% deadband is on 3.5. In Figure 2.18

the same simulation is performed by considering chattering instead of the summation.

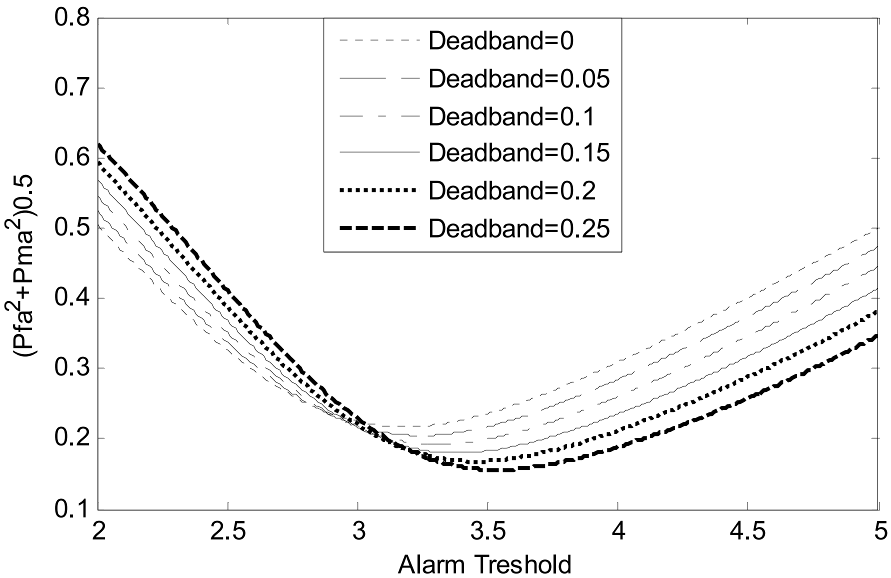


Figure 2.17: $(P_{ma}^2+P_{fa}^2)^{0.5}$ for different thresholds and deadbands for data in Figure 2.15

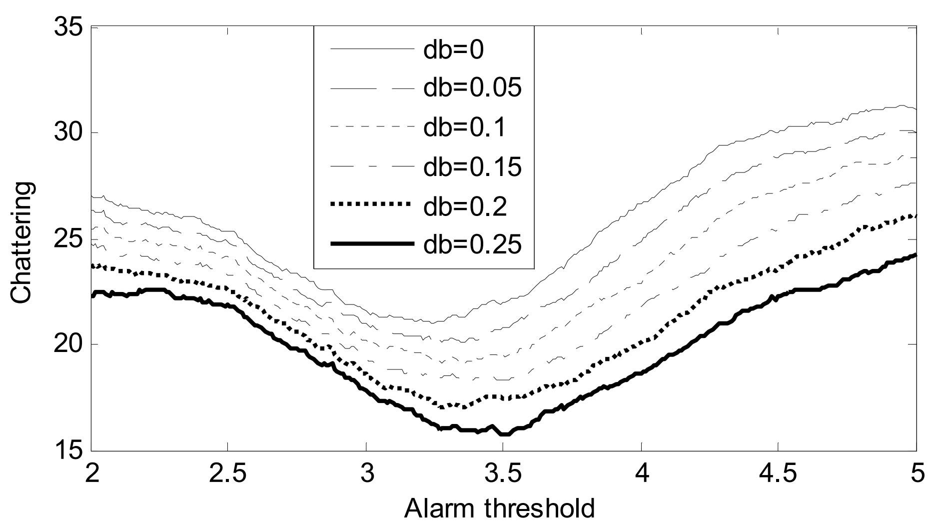


Figure 2.18: Chattering of the data in Figure 2.15

In Figure 2.18 the optimal thresholds corresponding to the least chattering are close to the ones in Figure 2.17. However, because the simulation is performed on just one set of data, the randomness of the data makes the chattering curves unsmooth.

Another similar simulation is performed on the data in Figure 2.19. The mean values of the two parts of the data are the same as the two previous examples and it has standard deviation of 2 in the normal part and 1 in its abnormal part.

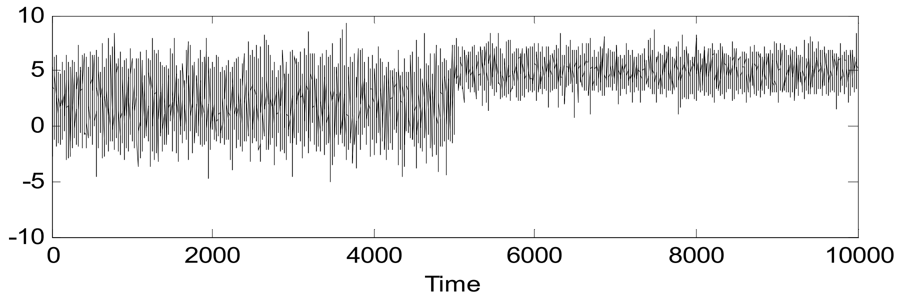


Figure 2.19: Simulated process data

Figure 2.20 depicts the summation for deadbands from zero to 0.25 and thresholds from 2 to 5. By comparing Figure 2.20 with Figure 2.13 it is observed that the increase in the standard deviation of the normal part of the data has made the optimal thresholds to move toward the abnormal part of the data.

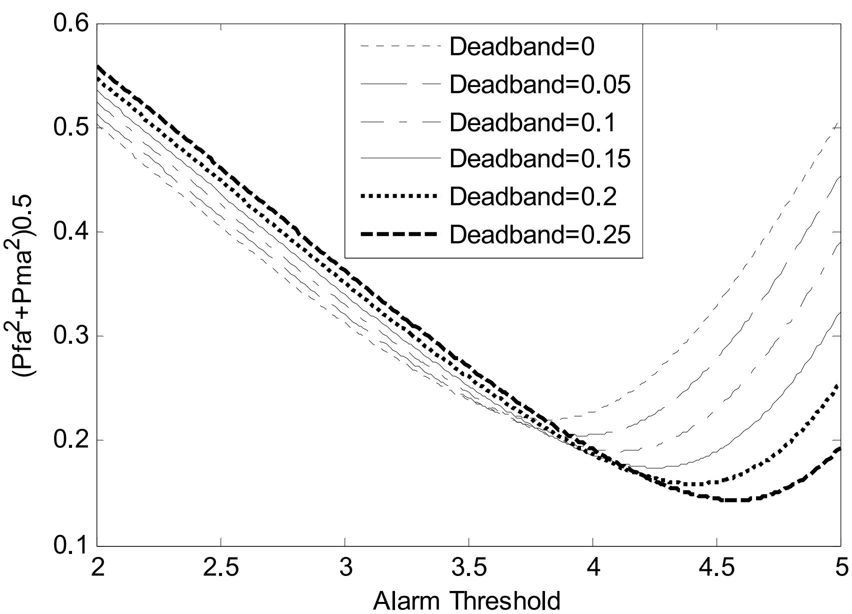


Figure 2.20: $(P_{ma}{}^2+P_{fa}{}^2)^{0.5}$ for the data in Figure 2.19

2.5 Effect of the deadband on false and missed alarm rates considering low alarms

In the low alarm case, the mean value of the abnormal part of the data is lower than the mean value of its normal part. The same simulations as in the previous section are performed considering the low alarm case. For example, consider the data in Figure 2.21. The first half of the data is its normal part with mean value of 5 and standard deviation of 1. The second half of the data is its abnormal part with mean of 2 and standard deviation of 1.

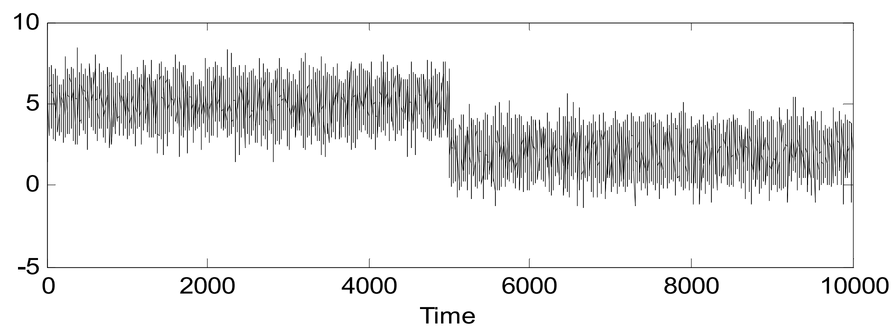


Figure 2.21: Simulated process data

In Figure 2.22 the PDF of the normal and abnormal parts of the data are depicted along with the alarm threshold and deadband limit.

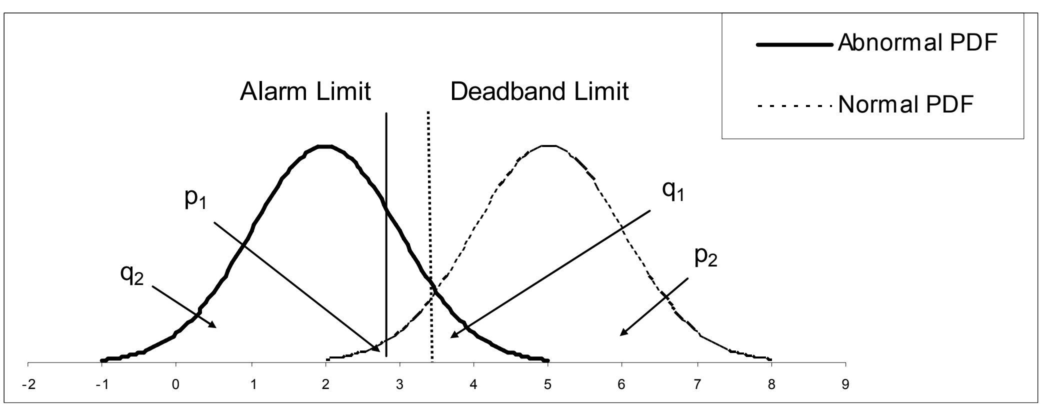


Figure 2.22: PDF of normal and abnormal parts of a simulated data with low alarm

The probabilities are calculated as follows for the case of low alarm:

$$p_1 = 0.5 + 0.5 erf\left(\frac{L - \mu_n}{\sqrt{2}\sigma_n}\right) \qquad p_2 = 0.5 - 0.5 erf\left(\frac{L(1+db) - \mu_n}{\sqrt{2}\sigma_n}\right) \tag{2.6}$$

$$q_1 = 0.5 - 0.5 erf\left(\frac{L(1+db) - \mu_a}{\sqrt{2}\sigma_a}\right) \qquad q_2 = 0.5 + 0.5 erf\left(\frac{L - \mu_a}{\sqrt{2}\sigma_a}\right) \tag{2.7}$$

Figure 2.23 depicts the summation of squared false and missed alarm rates for 6 different deadbands and thresholds from 2 to 5 considering the data in Figure 2.21.

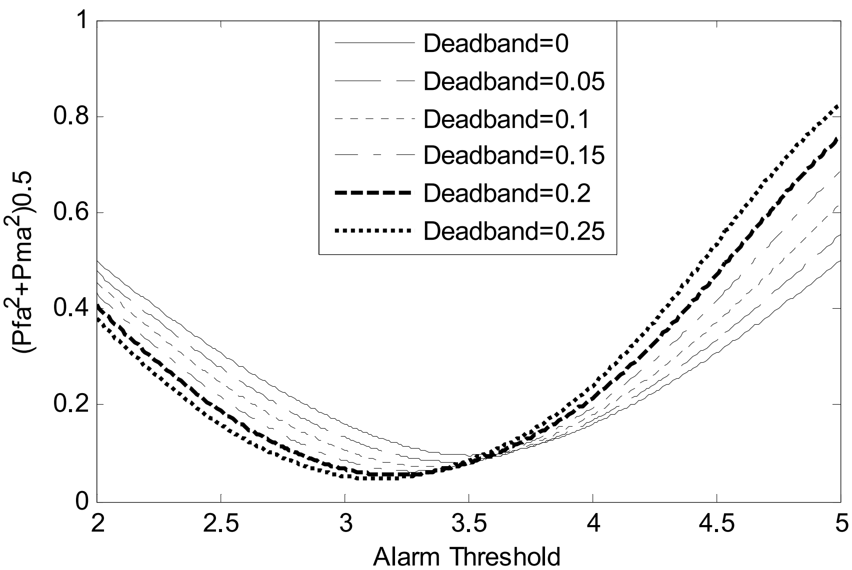


Figure 2.23: $(P_{ma}^2+P_{fa}^2)^{0.5}$ for different thresholds and deadbands for data in Figure 2.21

From Figure 2.23 it is seen that by increasing the deadband, optimal thresholds corresponding to the least summation, move to the left hand side which is closer to the mean value of the abnormal part of the data.

The same simulation is performed while the standard deviation of the abnormal part of the data is increased to 2. The data is plotted in Figure 2.24.

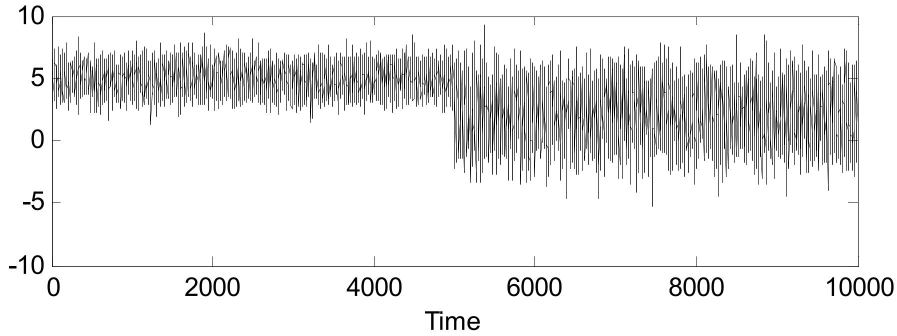


Figure 2.24: Simulated process data

In Figure 2.25 the summation is plotted for thresholds from 2 to 5 with 6 different deadbands considering the data in Figure 2.24.

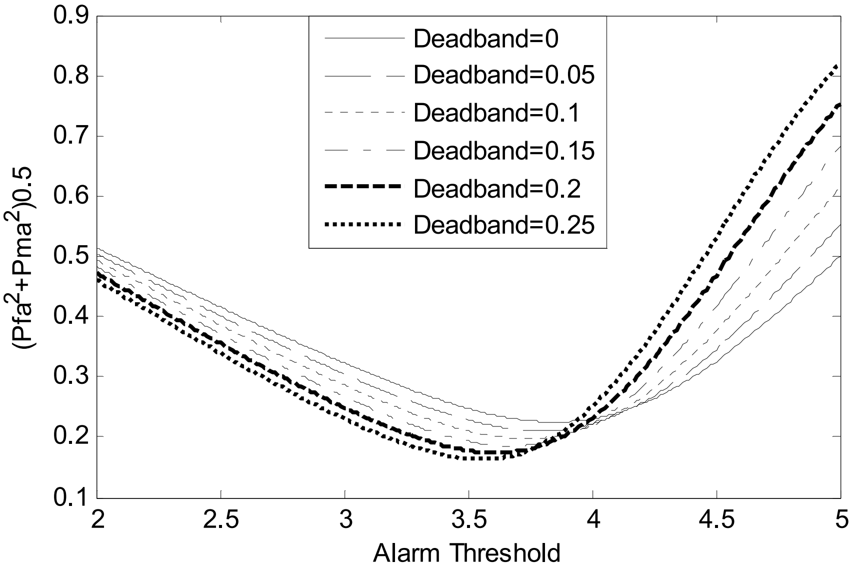


Figure 2.25: $(P_{ma}^2+P_{fa}^2)^{0.5}$ for different thresholds and deadbands for data in Figure 2.23

By comparing Figure 2.25 with Figure 2.23, it can be seen that the optimal thresholds in Figure 2.25 are moved to the normal part of the data for approximately 0.5 unit. This is because of the greater standard deviation in the abnormal part of the data.

This simulation is repeated for the data in Figure 2.26. Mean values of normal and abnormal parts of this data are the same as the previous two examples. The standard deviation of its normal part is 2 while the standard deviation of its abnormal part is 1.

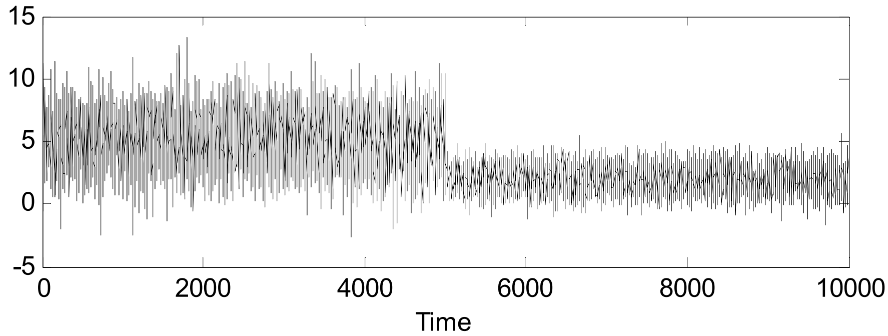


Figure 2.26: Simulated process data

Figure 2.27 shows the summation of false and missed alarm rates for thresholds from 2 to 5 with 6 different deadbands. By comparing Figure 2.27 with Figure 2.23, it is seen that the optimal thresholds are closer to the abnormal part of the data due to the increase in the standard deviation of the normal part.

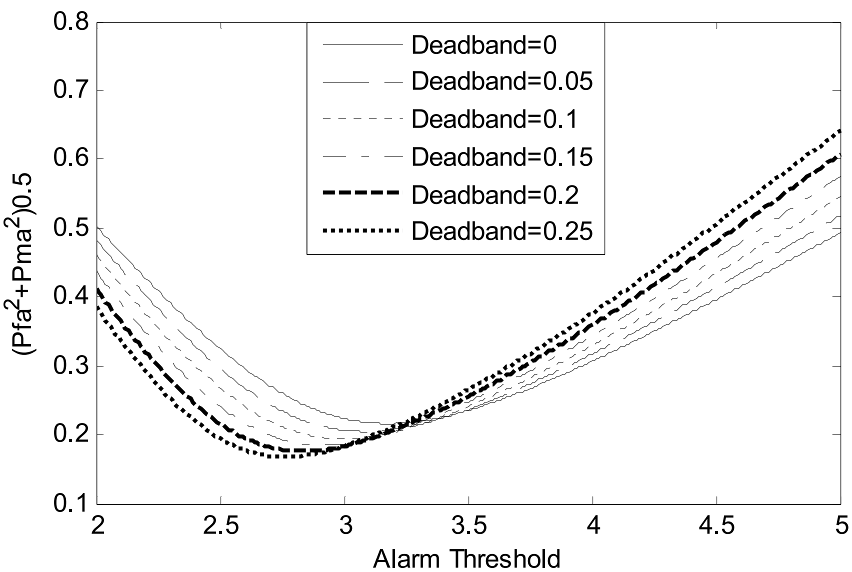


Figure 2.27: $(P_{ma}^2+P_{fa}^2)^{0.5}$ for different thresholds and deadbands for data in Figure 2.26

In this section it was shown that the design of deadband is very sensitive to the alarm threshold. For a fixed threshold it is possible that by increasing the deadband not only false and missed alarm rates along with chattering may not reduce, but, it may also result in their increase. So, the next section is about estimating the optimal alarm threshold based on the deadband value and statistical characteristics of the data.

2.6 Estimating the optimal threshold with respect to the deadband and statistical characteristics of the data

First the case of zero deadband is considered. The goal is to find the optimal threshold for zero deadband based on the statistical characteristics of the data. The optimal threshold, as was mentioned before is the one that minimizes $(P_{\mathrm{ma}}^2 + P_{\mathrm{fa}}^2)^{0.5}$. As the minimum of $(P_{\mathrm{ma}}^2 + P_{\mathrm{fa}}^2)^{0.5}$ is the same as the minimum of $(P_{\mathrm{ma}}^2 + P_{\mathrm{fa}}^2)$, the following equation holds at the optimal threshold.

$$\frac{d\,(P_{\mathrm{ma}}^2 + P_{\mathrm{fa}}^2)}{d\,L} = 0 \tag{2.8}$$

In the case of zero deadband p_1+p_2 and q_1+q_2 are equal to one. As a result $p_{fa} = p_1,\ p_{ma} = q_1$ and equation (2.8) simplifies to

$$2\,p_1 \frac{d\,p_1}{d\,L} + 2q_1 \frac{d\,q_1}{d\,L} = 0 \tag{2.9}$$

By assuming a Gaussian distribution model for the data (the case of high alarm)

$$\frac{d\,p_1}{d\,L} = \frac{-L}{\sqrt{2\pi}\sigma_n} e^{-(\frac{L-\mu_n}{\sqrt{2}\sigma_n})^2},$$

$$\frac{d\,q_1}{d\,L} = \frac{L}{\sqrt{2\pi}\sigma_a} e^{-(\frac{L-\mu_a}{\sqrt{2}\sigma_a})^2}.$$

Substituting the mathematical expressions of p_1 and q_1 and their derivatives, equation (2.9) becomes as:

$$(0.5-0.5erf(\frac{L-\mu_n}{\sqrt{2}\sigma_n}))\frac{1}{\sigma_n}e^{-(\frac{L-\mu_n}{\sqrt{2}\sigma_n})^2}=(0.5+0.5erf(\frac{L-\mu_a}{\sqrt{2}\sigma_a}))\frac{1}{\sigma_a}e^{-(\frac{L-\mu_a}{\sqrt{2}\sigma_a})^2}$$

This equation can not be analytically solved for the optimal threshold. So, using an approximation is necessary to find an estimation of the optimal threshold. For zero deadband the ROC curve is almost symmetric. So, the threshold corresponding to the minimum distance from the origin is usually very close to the threshold where false and missed alarm rates are equal. Thus, the solution to p_1=q_1 can approximate the solution of equation (2.9).

By replacing p_1 and q_1 by their mathematical expression the following equation is obtained:

$$0.5-0.5erf(\frac{L-\mu_n}{\sqrt{2}\sigma_n})=0.5+0.5erf(\frac{L(1-db)-\mu_a}{\sqrt{2}\sigma_a})$$

which can be simplified to:

$$-erf(\frac{L-\mu_n}{\sqrt{2}\sigma_n})=erf(\frac{L(1-db)-\mu_a}{\sqrt{2}\sigma_a})$$

As error function is an odd function, it is concluded that

$$-\frac{L-\mu_n}{\sqrt{2}\sigma_n}=\frac{L(1-db)-\mu_a}{\sqrt{2}\sigma_a}.$$

By solving this equation the threshold is obtained as:

$$L=\frac{\mu_n\times\sigma_a+\mu_a\times\sigma_n}{\sigma_n+\sigma_a} \qquad (2.10)$$

This threshold is exactly the threshold where false and missed alarm rates are equal for zero deadband. Since it is not exactly the threshold corresponding to the minimum summation, regression method is used to obtain a better estimation for the optimal threshold.

Since p_1, p_2 and also q_1, q_2 have different definitions for high and low alarm cases, the equation for optimal threshold would be different in the two cases. So, curve fitting is performed separately for high and low alarms.

About 30000 data sets with different statistical characteristics were generated by simulation for each case of high and low alarms. For each data set the optimal threshold was obtained by mathematically minimizing $(P_{\mathrm{ma}}^2 + P_{\mathrm{fa}}^2)^{0.5}$. The structure of the function for estimating the optimal threshold was inferred from equation (2.10), as is shown below. Parameters $\alpha_1 ... \alpha_4$ are the parameters to be estimated to get the best equation for estimating the optimal threshold.

$$L = \frac{\alpha_1 \times \mu_n \sigma_a + \alpha_2 \times \mu_a \sigma_n}{\alpha_3 \times \sigma_n + \alpha_4 \times \sigma_a}$$

Since in the first modeling α_1 and α_2 were estimated very close to one, their values were fixed on one and the regression method was repeated to get a better estimate of the parameters α_3 and α_4. The equation obtained for the high alarm case is:

$$L = \frac{\mu_n \times \sigma_a + \mu_a \times \sigma_n}{1.2\sigma_n + 0.8\sigma_a} \tag{2.11}$$

The equation obtained for the low alarm is:

$$L = \frac{\mu_n \times \sigma_a + \mu_a \times \sigma_n}{0.95\sigma_n + 1.13\sigma_a} \tag{2.12}$$

The same procedure was used to get the equations to estimate the optimal thresholds with nonzero deadband values. For each high and low alarm cases, about 160000 data sets was generated with different deadbands between 0 to

0.4. For each data set, the optimal threshold was obtained by minimizing $(P_{\mathrm{ma}}^2 + P_{\mathrm{fa}}^2)^{0.5}$.

The structure considered as the model in the regression is:

$$optimal\ L = \frac{\alpha_1 \mu_n \sigma_a + \alpha_2 \mu_a \sigma_n + \alpha_3 db\, \mu_a \sigma_n}{\alpha_4 \sigma_n + \alpha_5 db \sigma_n + \alpha_6 \sigma_a + \alpha 7\, db\, \sigma_a}$$

The reason for considering this model for performing regression is inferred from the result of the simulations that was shown before. It was seen that by increasing the deadband, the optimal threshold always moves toward the abnormal part of the data and its movement is restricted by the standard deviations of normal and abnormal parts of the data. So a weight with respect to the deadband is added to the mean value of the abnormal part of the data in the numerator of the equation and some weights to both normal and abnormal standard deviations in the denominator.

The parameters $\alpha_1 ... \alpha_3$ were estimated very close to 1 in the first performance of the regression. So, their values were fixed on one and the regression was again performed to get the parameters $\alpha_4 ... \alpha_7$.

For the case of high alarm, the equation is obtained as:

$$optimal\ L = \frac{\mu_n \sigma_a + (1 + db)\, \mu_a \sigma_n}{1.2 \sigma_n + (0.8 + 0.27\, db)\, \sigma_a} \tag{2.13}$$

If the deadband is zero, the equation becomes as equation (2.10). Figure 2.28 depicts the optimal thresholds obtained by mathematical optimization that were used for regression versus the optimal thresholds obtained by equation (2.13).

By fitting a linear model between optimal thresholds and estimated ones, their relation is obtained as L=0.995*ESTL+0.000. L is the real optimal threshold and ESTL is the estimated one.

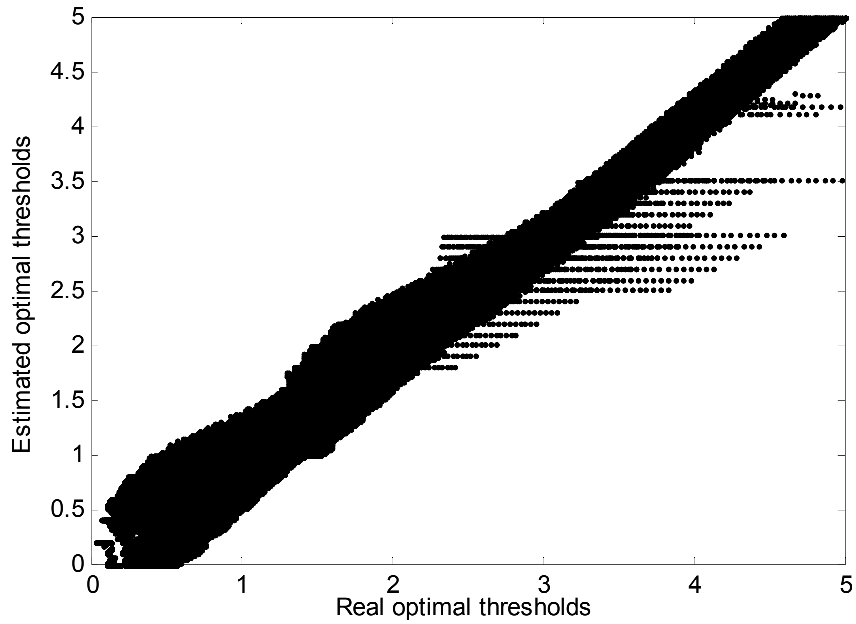


Figure 2.28: Estimated optimal thresholds versus the real ones for high alarm

The same procedure of modeling is performed for the case of low alarm. The equation for optimal threshold in this case is obtained as follows.

$$optimal\ L = \frac{\mu_n \sigma_a + (1+db)\,\mu_a \sigma_n}{0.95\sigma_n + (1.13 + 1.08\,db)\times\sigma_a} \tag{2.14}$$

This equation is the same as equation (2.10) for zero deadbands. Figure 2.29 plots the estimated optimal thresholds versus the optimal thresholds obtained by optimization. The relation between optimal thresholds with their estimation is obtained as L=1.001*estL-0.014.

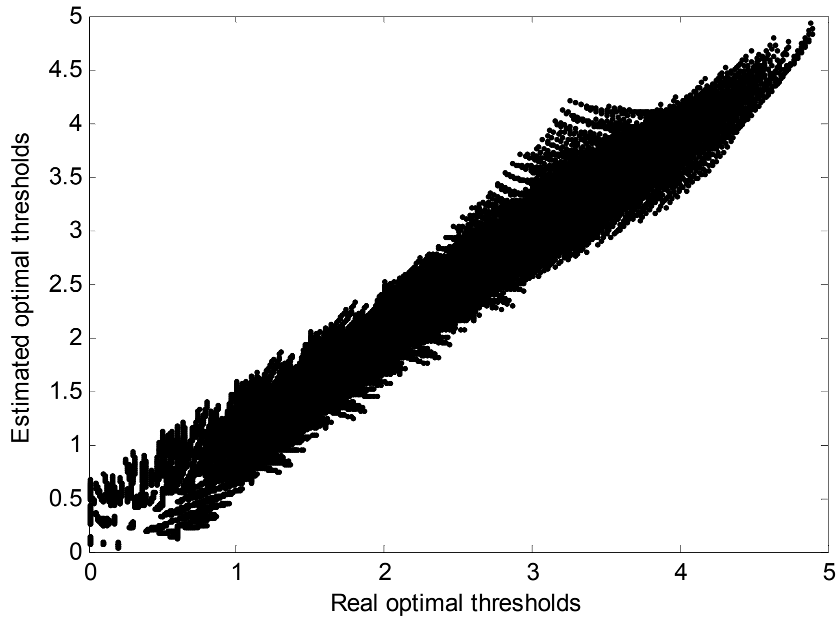


Figure: 2.29: Estimated optimal thresholds versus the real ones for low alarm

In both high and low alarm cases the real optimal thresholds have approximately identical relationship with the estimated thresholds.

To see the closeness of estimated optimal thresholds to the optimal thresholds based on the chattering, some simulation results are shown here. The statistical characteristics of the process data sets used in simulations are listed in Table 2.1.

In simulations the deadband is varying between 0.0 and 0.4. For every deadband, the threshold is moving from the mean value of the normal part to the mean value of the abnormal part of the data. Optimal thresholds based on the least chattering and the least summation of squared false and missed alarm rates are obtained in the simulations. The results are depicted in Figures 2.30 and 2.31. Figure 2.30 plots the estimated optimal thresholds by equations (2.13) and (2.14) versus the optimal threshold obtained by mathematical optimization of

$(P_{\mathrm{ma}}^2 + P_{\mathrm{fa}}^2)^{0.5}$. Figure 2.31 depicts the estimated thresholds versus the thresholds based on the least chattering.

Table 2.1: Statistical characteristics of simulated data sets

μ_n	μ_a	σ_n	σ_a
1	3	0.5	0.5
1	3	1	1
1	3	1.5	1
1	3	1	1.5
1	2	0.5	1
2	5	1	1
2	5	1	2
2	5	2	1
2	5	2	2
4	2	1	1.5
4	2	1.5	1

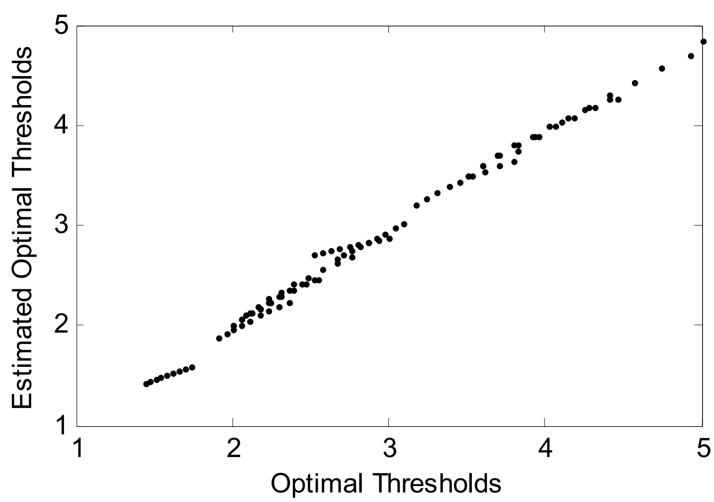


Figure 2.30: Estimated optimal thresholds versus the real thresholds for the data sets in Table 2.1

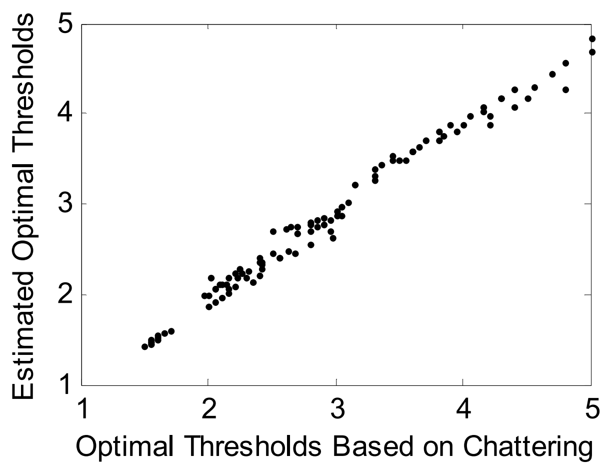


Figure 2.31: Estimated optimal thresholds versus the optimal thresholds based on chattering for data sets in Table 2.1

From Figures 2.30 and 2.31 it is seen that the optimal thresholds based on chattering are very close to the optimal thresholds based on the least distance from the origin in the ROC curve and the equations are successful in approximating the optimal thresholds based on the two definitions.

2.7 Relation between the optimal deadband with the alarm threshold and statistical characteristics of the data

In this section the relation between optimal deadbands (in terms of minimizing $(P_{\mathrm{ma}}^2 + P_{\mathrm{fa}}^2)^{0.5}$) with alarm thresholds and statistical characteristics of the data is investigated. To get a view of this relationship some simulation examples are shown here.

In the examples, the alarm threshold is moving from the mean value of the normal part of the data to the mean value of the abnormal part of the data. For each threshold, the optimal deadband is calculated by minimizing $(P_{\mathrm{ma}}^2 + P_{\mathrm{fa}}^2)^{0.5}$.

In the optimization procedure the deadband is limited between 0 and 0.5. The result of the simulation for the data in Figure 2.11 is shown in Figure 2.32.

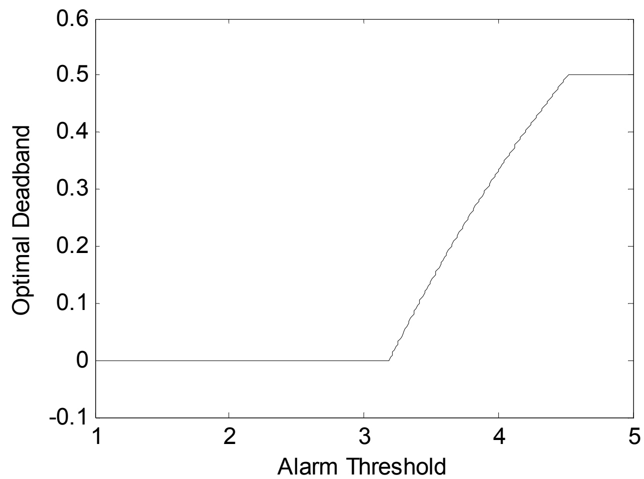


Figure 2.32: Optimal deadband versus the alarm threshold for the data in Figure 2.11

As is seen in Figure 2.32, the optimal deadband is zero for the thresholds less than 3.2 and then it linearly increases with the threshold until it hits its maximum value.

The same simulation is performed on the data in Figure 2.15. Figure 2.33 shows the result of the simulation in this case.

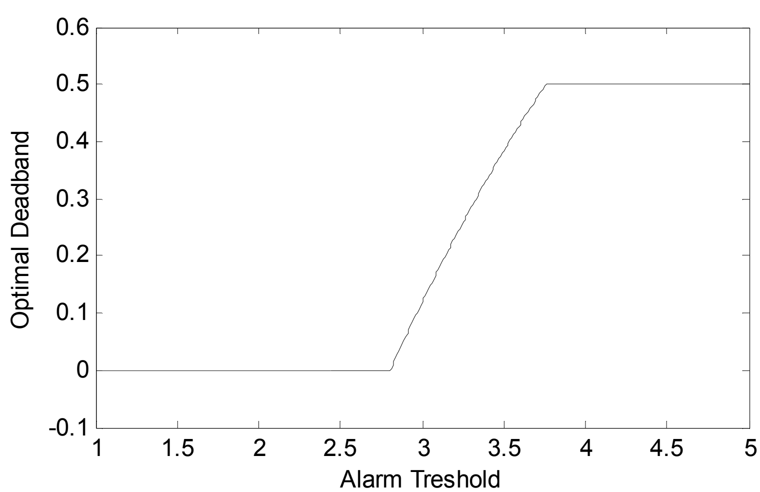


Figure 2.33: Optimal deadband versus the alarm threshold for the data in Figure 2.15

In Figure 2.33 the same features as in Figure 2.32 are seen. The difference is that in this figure, the optimal deadband starts increasing from zero when the threshold is on 2.8 and then increases with a higher slope compared to Figure 2.31. This is the result of higher standard deviation in the abnormal part of the data.

The result of another simulation is shown here to see the effect of the higher standard deviation in the normal part of the data on this relationship. Figure 2.34 shows the result of the same simulation for the data in Figure 2.19. The deadband starts increasing from zero at a higher threshold value and continues increasing with a lower slope compared with the two previous examples.

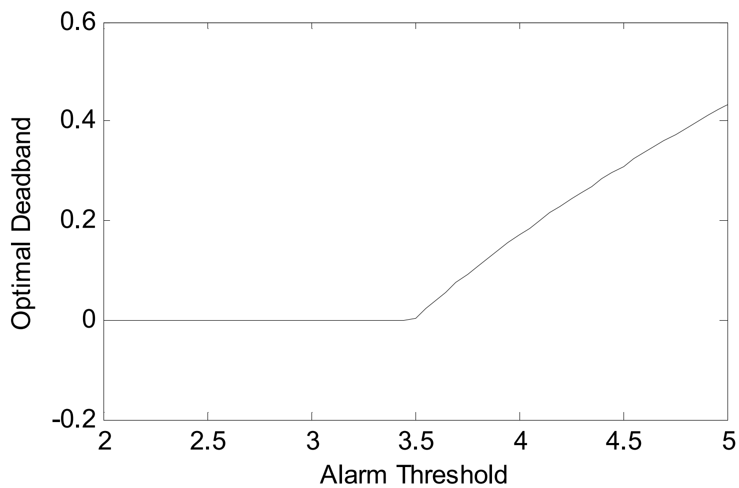


Figure 2.34: Optimal deadband versus the alarm threshold for the data in Figure 2.19

Now we try to analytically find the optimal deadband. As was mentioned, the optimal deadband is the one that minimizes $(P_{\mathrm{ma}}^2 + P_{\mathrm{fa}}^2)^{0.5}$, which is the same one minimizing $(P_{\mathrm{ma}}^2 + P_{\mathrm{fa}}^2)$. So, the fowling mathematical equations hold for the optimal deadband.

$$\frac{d(P_{fa}^2+P_{ma}^2)}{d(db)}=\frac{d(\frac{p_1}{p_1+p_2})^2}{d(db)}+\frac{d(\frac{q_1}{q_1+q_2})^2}{d(db)}=0$$

$$-2p_1^2(q_1+q_2)^3\frac{d(p_2)}{d(db)}+2q_1q_2(p_1+p_2)^3\frac{d(q_1)}{d(db)}=0 \qquad (2.15)$$

where (considering high alarm case)

$$p_1=0.5-0.5erf(\frac{L-\mu_n}{\sqrt{2}\sigma_n}), \qquad p_2=0.5+0.5erf(\frac{L(1-db)-\mu_n}{\sqrt{2}\sigma_n})$$

$$q_1=0.5+0.5erf(\frac{L(1-db)-\mu_a}{\sqrt{2}\sigma_a}), \qquad q_2=0.5-0.5erf(\frac{L-\mu_a}{\sqrt{2}\sigma_a})$$

$$\frac{d(p_2)}{d(db)}=\frac{-L}{\sqrt{2\pi}\sigma_n}e^{-(\frac{L(1-db)-\mu_n}{\sqrt{2}\sigma_n})^2}, \qquad \frac{d(q_1)}{d(db)}=\frac{-L}{\sqrt{2\pi}\sigma_a}e^{-(\frac{L(1-db)-\mu_a}{\sqrt{2}\sigma_a})^2}$$

As can be seen in the above formulas, db is present in both the error function and exponential function. So, the equation can't be analytically solved for the optimal deadband. However, the optimal deadband can be obtained by numerically solving the equation (2.15).

3 Estimation of the chattering index

3.1 Introduction to chattering index

As was mentioned in Chapter 1 and Chapter 2, chattering is repetition of an alarm in a short time interval. However, there is no precise definition to determine how many alarms per minute is considered chattering. Industrial engineers usually call an alarm that repeats more than two times in a minute as a chattering alarm.

Chattering alarms are the highest contributors to alarm floods. Alarm floods are generally defined as a condition in which the number of received alarms is higher than the maximum number that the operator can response to. For example receiving more than 10 alarms per 10 minute [1] is called alarm flood. Alarm floods usually happen due to simultaneous announcement of some chattering tags along with some other tags. However, most of the announced alarms are the chattering ones. So, it is important to identify chattering alarms and redesign alarm parameters to reduce the chattering.

Redesigning of the alarm threshold can be very helpful in chattering reduction. However, in most cases the alarm threshold is not changeable. So the preprocessing techniques such as filters, delay timers and alarm deadbands are usually used to reduce the chattering.

There are some general rules for the design of filters, delay timers and deadbands in standards. But, the problem is that these rules can not always generate the best result and some precise method for the design is necessary to get a good result.

A reason for lack of the analytical design methods is the lack of analytical relation between chattering and the design parameters. To find the analytical relation between chattering and alarm parameters, using a quantitative definition for chattering is necessary. In this work, the definition presented in [13] is considered.

As was mentioned in Chapter 1, this chattering index is based on constructing the alarm run length distribution from the alarm database. The run length, in the case of alarm management, is the time difference between successive alarms. The time differences can be calculated from the alarm database. The number of repetition of every specific run length is called alarm count. The run length distribution is a plot of the alarm counts versus the run lengths.

For example, the run length distribution of a simulated process data, which is depicted in Figure 3.1, is shown in Figure 3.2. The alarm threshold is at 3.0 and no preprocessing technique is used.

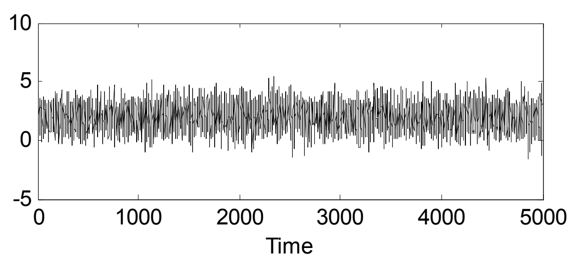


Figure 3.1: Simulated process data

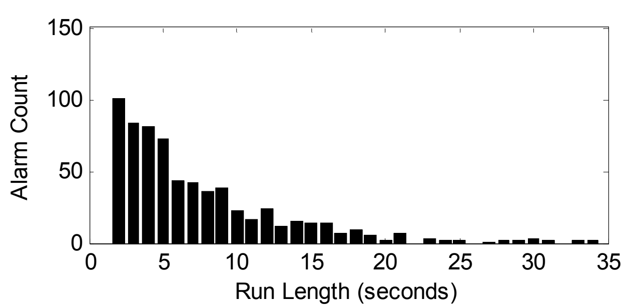


Figure 3.2: Run length distribution of simulated data in Figure 3.1

The chattering index is defined as a weighted sum of alarm counts, divided by the total number of alarm counts. The weighting function should give more weight to the small run lengths and attenuate the effect of larger ones.

A small run length means the alarm repeats in a very short time interval which is considered as high chattering. A large run length means there is a large time difference between the two alarms, so, it might not be considered as chattering. So, the effect of smaller run lengths should be highlighted in calculation of alarm chattering. The weighting function is considered as the inverse of the run lengths.

The chatter index is then defined as $\dfrac{\sum_r \frac{AC_r}{r}}{\sum_r AC_r}$.

AC is abbreviation of Alarm Counts and r is abbreviation of Run Length.

This chattering index gives a number between zero (no chattering) and one (as the maximum amount of chattering). The maximum chattering happens when the alarm repeats in every second (assuming the sampling interval is 1 second) during the total time period. One advantage of this chattering index is that it doesn’t have any parameter.

A reasonably large time interval should be considered for obtaining the run length distribution to have a fair measurement of the alarm chattering. Using this chattering index provides the ability to compare the alarm variables and to identify the most occurring tags.

3.2 Probability analysis of alarming

The basis of the chattering index is the run length distribution. While we have the run length distribution, chattering can be calculated in any preferred way. So, this section is about estimation of the alarm run length distribution from the process variable.

It is first assumed that the process data is an iid (independent and identically distributed) noise with a known distribution. For example consider a simulated data with a Gaussian distribution as is depicted in Figure 3.3. Also a nominal alarm threshold is depicted in the figure. The probability of any sample of the data to fall above the alarm threshold is noted by P_1. In this example P_1 is 0.12.

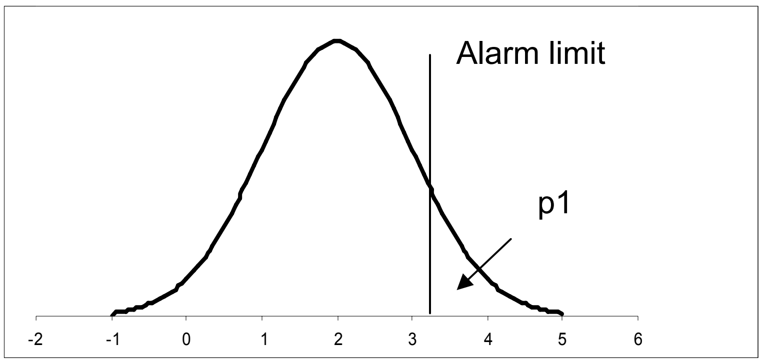


Figure 3.3: Probability distribution function of a Gaussian distributed data

Since it is assumed that the data is iid, from the probability point of view, every sample of the data is similar to a Bernoulli experiment with two outcomes; falling above the alarm threshold or beneath the alarm threshold.

In probability and statistics theory, Bernoulli trial is an experiment with a random outcome between its two possible random outcomes: success or fail. For example for the data in Figure 3.3, if assuming that the success is falling above the alarm threshold, then the probability of success is 0.12.

In probability and statistics theory, a sequence of identical and independent Bernoulli trials with the same distribution is known as Bernoulli process. So, the process data that includes n samples (Bernoulli trials) is similar to a Bernoulli process (assuming the data is independent and identically distributed).

From the alarm management perspective, the number of times that the alarm transits from off state to on state is more important than the number of samples above the alarm threshold. So, hereafter the probability of success is considered as the probability of alarm rise.

Alarms happen when the measurement transits from the normal range to the abnormal range. So, when there is no processing done on the measurement, the probability of alarm, (which will be noted by P_A), is equal to the probability of a sample being above the alarm threshold while the previous sample was lower than the alarm threshold. For example, considering the process data in Figure 3.3 this probability can be calculated as follows:

$P_A = P(\text{xi=on,xi-1=off}) = P(\text{xi-1=off}) * P(\text{xi=on}) = P_1(1- P_1)$

As a known fact in probability theory, number of occurrences of "successes" (event under study) in a Bernoulli process has a Binomial distribution. A Binomial random variable is defined as "a random variable that denotes the number of 'successes' in n Bernoulli trials" [14]. The PDF (probability distribution function) of this distribution is

$$P(x) = \binom{n}{x} q^x (1-q)^{n-x} \qquad x = 0,1,2,\ldots,n \tag{3.1}$$

where n is the total number of Bernoulli trials and q is the probability of 'success' in every experiment. The expected value of the Binomial random variable is stated as nq.

For the case of alarming, if assuming the data is a Bernoulli process with alarming as 'success', the expected value of the Binomial distribution can give an estimation of number of alarms triggered by the process data. For the process data in Figure 3.3 an estimation of number of alarms is $nP_A = nP_1(1- P_1)$.

A special form of the Binomial distribution is called the Poisson distribution. If the number of Bernoulli experiments is large and the probability of “success” is small (roughly less than 0.1), the Binomial distribution can be approximated by Poisson distribution [14]. Poisson distribution is usually used in modeling the number of occurrences of events that have a constant average rate of occurrences. The PDF of the Poisson distribution is

$$P(x) = \frac{e^{-\lambda}\lambda^{x}}{x!} \qquad x = 0,1,... \tag{3.2}$$

λ is the expected number of occurrences of the event in the total time interval.

Since it is assumed that the distribution of the process data is constant, the Poisson distribution can make a good estimation of the number of alarms generated by the process data.

As a fact in probability theory, if the number of occurrences of an event has the Poisson distribution, the time differences between successive occurrences of the event have an exponential distribution model. The exponential distribution is widely used in estimation of systems or equipment’s lifetime or reliability as well as waiting times between occurrences of random events with a constant average rate [14]. The PDF of the distribution is

$$P(x) = \frac{1}{\beta} e^{-x/\beta} \qquad 0 < x < \infty \tag{3.3}$$

where β is the average waiting time.

Based on the previous discussion, by considering an alarm as the event under study, the distribution of waiting times between successive alarms has the exponential distribution (by assuming that the data is independent and identically distributed). This distribution is exactly the run length distribution of alarms that is used in the chattering index calculation. The only parameter of distribution, β, needs to be estimated from the distribution characteristic of the process data.

As mentioned before, the estimated number of alarms is obtained as the expected value of the Binomial distribution. β is then calculated by dividing n (length of the process data) to nP_A (expected value of the Binomial distribution) which is equal to $1/P_A$. By obtaining the alarm run length, chattering can be calculated as explained in section 3.1. Assuming the sample time of one second, the chattering index is:

$$\frac{\sum_{x=1}^{\infty} \frac{n}{x} \times P_A^2 \times \exp(-P_A \times x)}{n \times P_A} = \sum_{x=1}^{\infty} \frac{P_A}{x} \times \exp(-P_A \times x) \qquad (3.4)$$

For the process data in Figure 3.3 by replacing P_A with its derived value, the chattering index is obtained as

$$\sum_{x=1}^{\infty} \frac{(1-P_1)P_1}{x} \times \exp(-(1-P_1)P_1 \times x)$$

So under some specified conditions, the exponential distribution can be used to calculate the chattering from the distribution characteristics of the process data and alarm parameters.

3.3 Generalization of the result

The important assumption in deriving the distribution model of the alarm run length was that the process data is iid. In practice, this assumption does not hold if considering the whole process data history together.

In many cases the data contains abrupt changes. So, by eliminating the transition parts of the data it is possible to divide the data in parts with approximately constant distribution characteristics. As the signal during transition can't cause alarm chatter, this procedure doesn't reduce the precision of the estimation. By this technique, the process data in every part will be approximately iid, as it is only affected by noise. In practice, the distribution of the data is usually supposed to be Gaussian. So, the division should be based on mean changes of the process data.

An important condition of the Poisson distribution was mentioned as constant average rate of the event under study. This assumption holds if the distribution characteristics of the process data are constant. The rate of alarming obviously is not constant in different states of the process variable. However, by dividing the data in parts according to process states, the average rate of alarming will be constant in each part.

So, the procedure of alarm chattering calculation from the process data is as follows. Firstly, divide the data in parts according to the different operation states. Secondly, estimation of the distribution model of the data in each section and calculation of the probability of alarm in every data section. Thirdly, the run length distribution should be estimated separately for each part. Finally, run length of the whole process data is obtained by summing up all of the estimated run lengths together. Chattering of the process data can be calculated from the final run length distribution as explained in the previous section.

3.4 Derivation of alarm chattering formula with alarm deadbands

As was mentioned in Chapter 2, Alarm deadband means specifying two thresholds for triggering and clearing the alarm. The alarm goes on when the process variable exceeds the alarm threshold and clears when it passes the deadband limit.

For example, the PDF of a Gaussian distributed data is depicted in Figure 3.4 along with the alarm threshold and deadband limit. P_1 is the probability that a sample exceeds the alarm threshold and P_2 is the probability that a sample falls lower than the deadband limit.

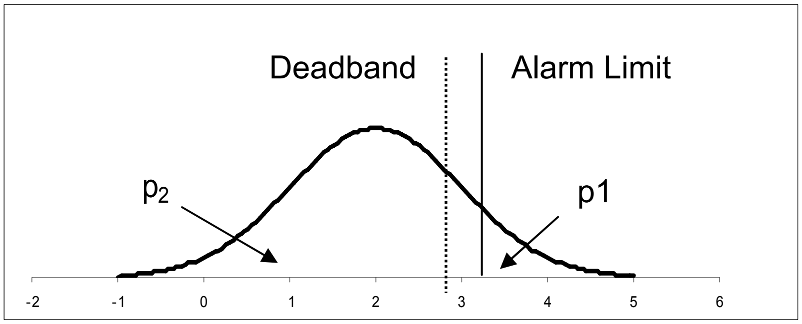


Figure 3.4: PDF of a Gaussian distributed data

To use the discussed method for estimating the chattering index with deadband, the probability of alarming with a deadband in the system needs to be calculated. Markov process for an alarm variable with a deadband is depicted in Figure 3.5. The probability of alarm rise, which is the probability of transition of the alarm state from no alarm to alarm, is $P(NA) * P_1 = \dfrac{P_2\, P_1}{P_1 + P_2}$.

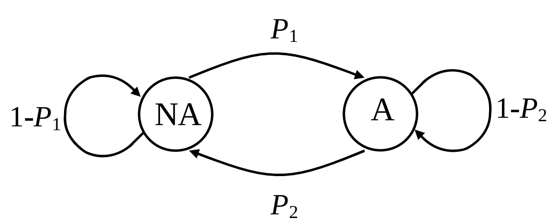


Figure 3.5: Markov diagram of a system with alarm deadband

As discussed in section 3.2, the expected number of alarms triggered by the variable is $num \times \dfrac{P_2\, P_1}{P_1 + P_2}$ (*num* is the number of data samples). So the chattering index is derived as

$$\sum_{x=1}^{\infty}\frac{1}{x}\left(\frac{P_2 P_1}{P_1+P_2}\right)\times\exp\left(-\frac{P_2 P_1}{P_1+P_2}\times x\right)$$

The equation is the same for different kinds of distributions. The difference is only in calculation of P_1 and P_2. Assuming the sample time is one and the alarm is recorded at every sample time, the minimum run length would be on 2 seconds with the existence of the deadband. It means that the least possible time difference between two alarms is two sample times.

3.5 Derivation of alarm chattering formula with time delay

Time delay is another useful method for chattering reduction. It can be applied in rising or clearing the alarm. In the case of on-delay timer, the alarm goes on if *n* consecutive data samples have exceeded the alarm limit. If there is off-delay timer configured in the system, the alarm clears only when *m* consecutive samples are lower than the alarm or deadband limit.

Markov process for the time delay case depends on the number of on and off delay timers. For example the Markov process for a system with three samples on-delay and two samples off-delay is depicted in Figure 3.6.

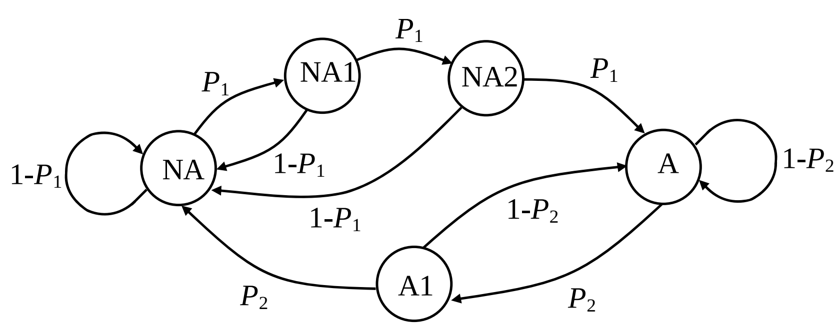


Figure 3.6: Markov diagram of a system with three samples on delay and two samples off delay

Assuming that the data is firstly in the normal range of operation, the alarm state is on the no alarm state (NA). If the next sample is again in the normal range with probability of 1-P_1 the alarm state remains in NA. The alarm state transits to NA1 while one sample exceeds the alarm limit with probability of P_1 (In this state the alarm is still off). If the next sample goes back to the normal range, the alarm state transits to NA, and if it is again in the abnormal range, the alarm state transits to NA2. The alarm becomes on in the case that another sample is in the abnormal range.

The same is true for clearing the alarm. The intermediate alarm state A1 happens while one sample has gone back to the normal range. However, the alarm remains on. If the next sample is in the normal range the alarm transits to the off state and if the sample is in the abnormal range the alarm goes back to A.

The probability of raising alarms in the case of the time delay equals to the probability of the last no alarm state (NA_{n-1}) multiplied to the probability of its transition to the alarm state (A). In this example the probability of alarming is $P_{(NA2)}$*P_1. For a system with n on-delay and m off-delay samples, the probability of the last no-alarm state can be obtained as [9]:

$$P(NA_{n-1}) = \frac{P_2^m \; P_1^{n-1}}{p_2^m \,(p_1^{n-1} + ... + P_1 + 1) + P_1^n \,(P_2^{m-1} + ... + P_2 + 1)} \quad (3.5)$$

So, the average number of alarms triggered by the variable would be

$$num \times \frac{P_2^m \; P_1^n}{p_2^m \,(p_1^{n-1} + ... + P_1 + 1) + P_1^n \,(P_2^{m-1} + ... + P_2 + 1)}$$

where num is the number of data samples. The chattering index is

$$\sum_{x=1}^{\infty} \frac{1}{x} \left(\frac{p_1^{\,n} \times p_2^{\,m}}{p_1^{\,n}(1 + p_2 + ... + p_2^{\,m-1}) + p_2^{\,m}(1 + p_1 + ... + p_1^{\,n-1})} \right) \exp\left(- \frac{p_1^{\,n} \times p_2^{\,m}}{p_1^{\,n}(1 + p_2 + ... + p_2^{\,m-1}) + p_2^{\,m}(1 + p_1 + ... + p_1^{\,n-1})} \times x \right)$$

This equation can also be used in cases of applying both time delay and alarm deadband with different kinds of distributions. Assuming one second sampling time, the minimum possible time difference between successive alarms would be $n+m-1$. So the alarm count is zero for run lengths less than $n+m-1$.

3.6 Simulation examples

Simulations are performed to compare the actual alarm chattering with its estimation using the proposed method. The simulated data is shown in Figure 3.7. It contains two Gaussian distributed parts. The first half of the data has a mean value of 1 and standard deviation of 1.5. The average of the second half of the data is 5 and the standard deviation is 2.

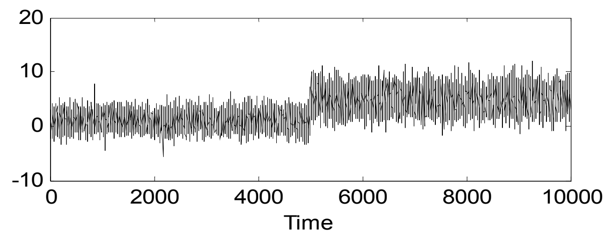


Figure 3.7: Simulated data

In the first simulation, the alarm threshold is on 2 and there is no alarm deadband or time delay. Probability of alarm in the first half of the data is 0.18 and in the second half is 0.06. The run length distribution is obtained for each part of the data separately. Monte Carlo simulation is used in calculation of the alarm run length. The run length distribution is obtained as the solid line in Figure 3.8 and the estimated run length (summation of the two run length distributions) is depicted in dashed line.

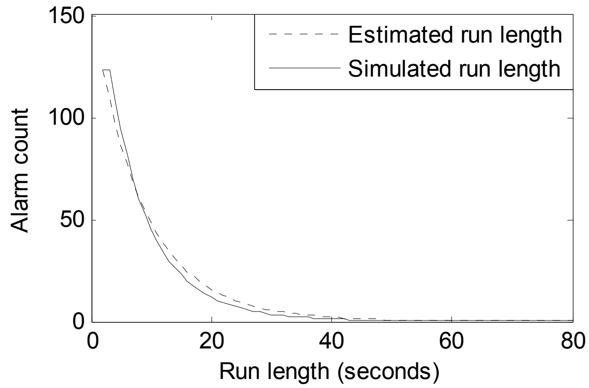


Figure 3.8: Run length distribution of a simulated data without any processing technique

Chattering is obtained as 0.194 from the simulation and 0.179 from the estimated run length.

In the second simulation the simulated data is as in the previous one. The alarm threshold is kept on two and an alarm deadband of 20% is applied on the system. Figure 3.9 shows the run length obtained from simulation in the solid line and the estimated run length is in the dashed line.

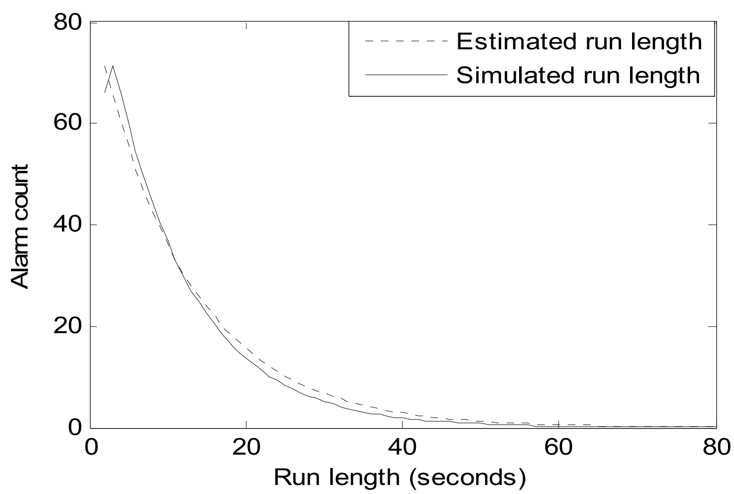


Figure 3.9: Run length distribution of a simulated data with alarm deadband

Chattering is obtained as 0.160 from simulation and 0.153 from the estimation.

In the third simulation the mean value and standard deviation of the data is 1 and 2 respectively in the first half, and 3 and 2 in the second half. The alarm threshold is on 2. The system has no deadband in this simulation, but, it has two sample on-delay and two sample off-delay timers. The alarm run length obtained in simulation is shown in Figure 3.10 in the solid line and the estimated run length is shown in the dashed line. Chattering is calculated as 0.089 from the simulation while the estimated one is 0.086.

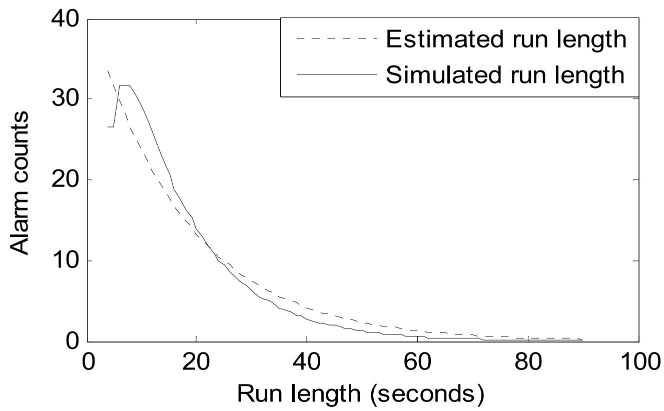


Figure 3.10: Run length distribution of a simulated data with time delay

In previous examples only Gaussian distributed data were considered. In the next example the data has Chi-Square distribution with 6 degrees of freedom. The PDF of the data is plotted in black dots in Figure 3.11.

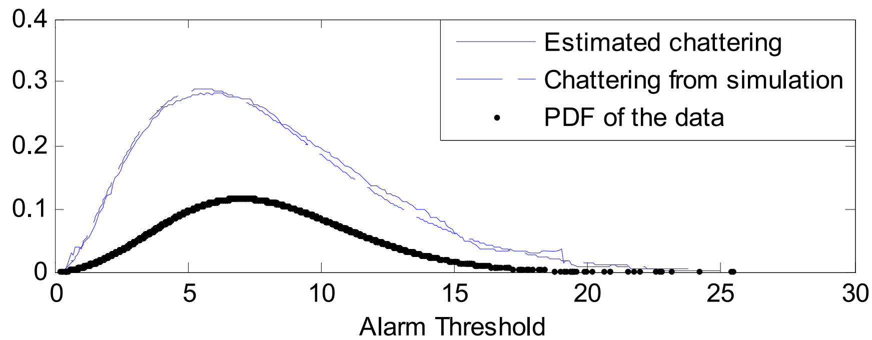
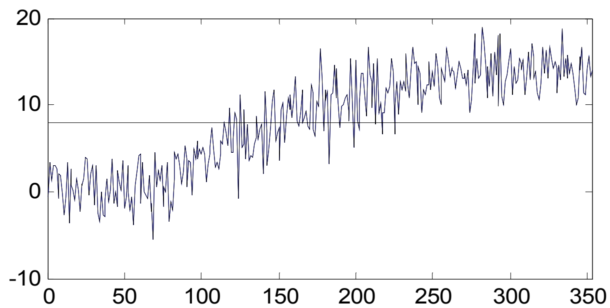


Figure 3.11: Chattering indexes for different thresholds considering a Chi-square distributed data

In the simulation, alarm threshold is moving from zero to 25 and there is 10% alarm deadband. Chattering is obtained in the simulation for every threshold and is plotted in solid line in Figure 3.11. Estimation of chattering is obtained for every threshold by using the proposed method and the estimated ones are plotted in dashed line in Figure 3.11. As can be seen in the figure, the estimations are very close to the real values of chattering.

In these simulations the case of abrupt changes in the process data was investigated. However, in many cases the process data has structure and slowly crosses the alarm threshold. One example is shown in Figure 3.12. The process data can be modeled as a structure with white noise. To be able to use the proposed methods for chattering estimation while testing different deadbands and time delays for this system, this process data needs to be replaced by an equivalent iid noise.



Figurer 3.12: Simulated data

By doing several simulations it is concluded that the best replacement for the data during transition from normal to abnormal parts is an iid noise with distribution parameters estimated from the data. For this purpose the part of the data during the transition should be considered for estimating a distribution model. The fitted distribution can be used instead of the real data for further analysis on the effect of alarm processing techniques on the chattering.

For the process data shown in Figure 3.12, a Gaussian distributed noise with parameters estimated from the part of the real data that causes the most alarm chattering (the data between the first alarm to the last alarm) is used to estimate the chattering while considering different deadbands and time delays. The estimated chattering amounts are listed in Table 3.1 besides the chattering amounts that are obtained by simulations. As it is seen the error of estimation is acceptable.

Table 3.1. Chattering amounts and their estimated values for different deadbands considering data in Figure 3 .12

Deadband	simulation	estimation
0	0.24	0.25
0.05	0.23	0.24
0.1	0.22	0.23
0.15	0.20	0.21
0.2	0.19	0.20
0.25	0.18	0.18
0.3	0.17	0.17

3.7 Application to alarm design

Analytical relation between chattering and alarm parameters makes it possible to perform an optimal design targeting the least chattering. The necessary knowledge for the design is the distribution characteristics of the data. After classifying the process data and estimating the distribution parameters for each part, the chattering index can be written as a mathematical equation with alarm parameters as its variables. The equation can be minimized by applying some optimization method to get the optimal parameters.

In cases that the mathematical optimization is not suitable, it is possible to get a better understanding on how chattering varies corresponding to variations of alarm parameters by evaluating the chattering equation for a range of alarm parameters. For instance, if the design of a deadband with a fixed alarm threshold is considered, the chattering indexes for different deadbands can be simply obtained by using the chattering equation and the best deadband can be chosen according to the situation.

For example, the data plotted in Figure 3.7 is considered. The goal is to both design a deadband and alarm threshold to minimize the chattering. So, the chattering index is calculated by using its mathematical expression for thresholds changing from the mean value of the normal part of the data to the mean value of its abnormal part considering different deadbands. Figure 3.13 shows how chattering varies with respect to changes in the threshold and deadband. If the limit of the maximum deadband and the acceptable range of the threshold are known, the best values of threshold and deadband can be easily obtained according to the plot.

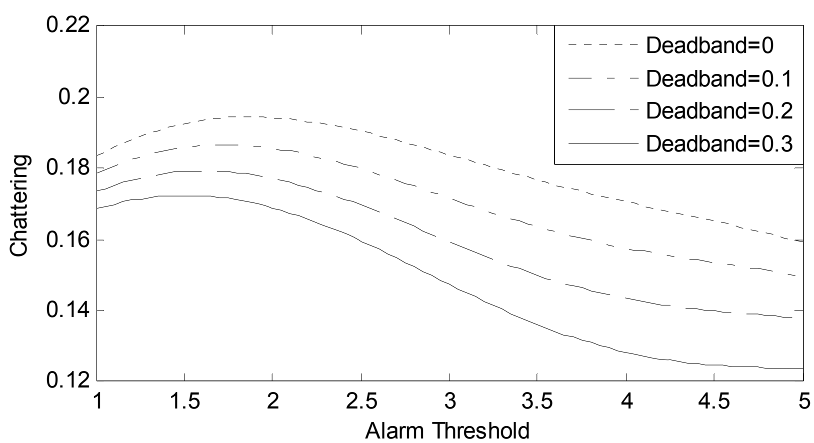


Figure 3.13: Chattering for different thresholds and deadbands considering the data in Figure 3.7

4 Case Studies

This chapter is about the application of the proposed methods in the last two chapters in alarm design. Two examples are presented discussing the application of the results on two industrial tags. The process data is provided by an industrial partner.

Since the length of the industrial process data is huge, it takes a lot of time to run simulations on the data to check the effect of possible alarm limits or deadbands on reduction of number of alarms and chattering. So, estimating the chattering index by the method presented in Chapter 3 can be quite helpful in redesigning the alarm parameters.

While the distribution characteristics of the process data are known, chattering and the number of alarms can be obtained for different alarm parameters within a few seconds. Following are two examples applying the method on two sets of industrial process data.

4.1 Example 1

The first example is an industrial flow measurement. The data, which is depicted in Figure 4.1 is sampled at every second over two days. The alarm threshold is on 12 and the original deadband is 0.23. It generates 75 low alarms in one hour and its chattering index is 0.09.

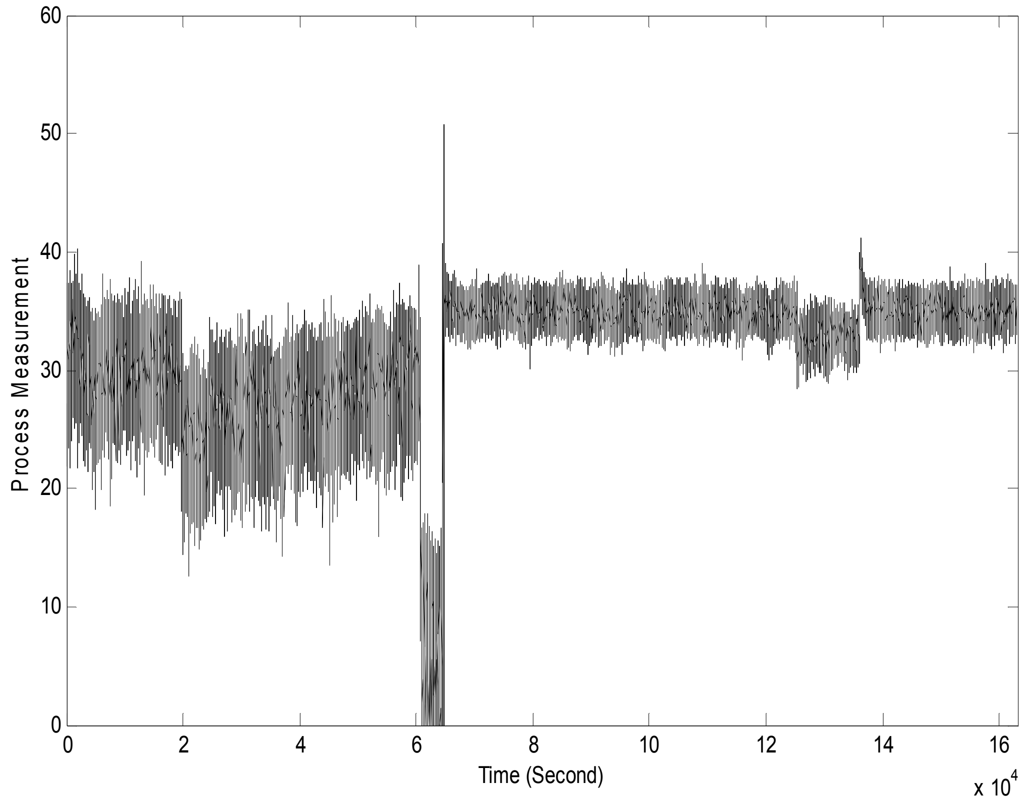


Figure 4.1: Industrial flow measurement

As was mentioned in Chapter 3, the first step to estimate the chattering is to divide the data in parts with approximately constant distribution characteristics. For this purpose the data is divided in 14 parts. Figures 4.2 and 4.3 depict the subsections of the data along with their mean and standard deviation values.

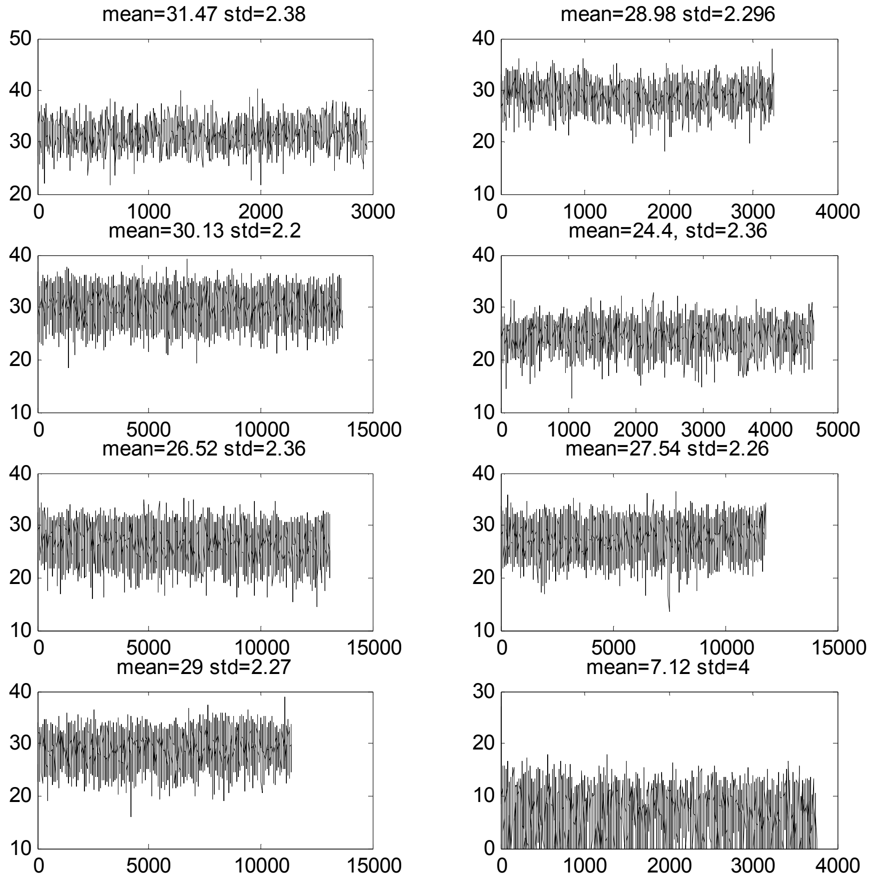


Figure 4.2: Subsections of the data in Figure 4.1

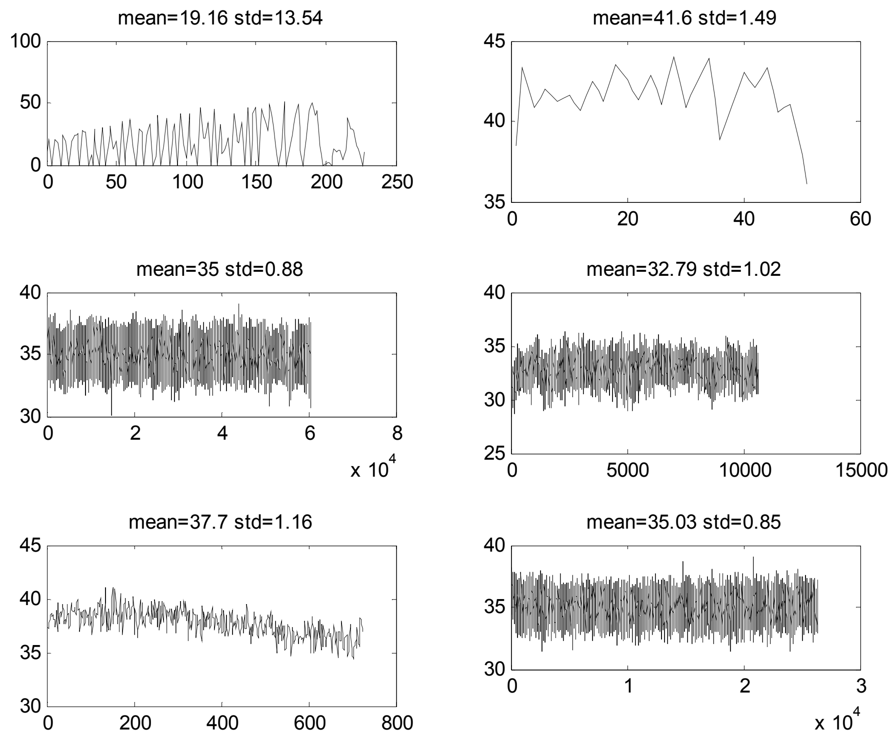


Figure 4.3: Subsections of the data in Figure 4.1

The variance of the data in the top left plot in Figure 4.13 is constantly increasing. So this section of the data is also divided in 5 parts with less change in their standard deviation.

The next step after dividing the data is to obtain the equation of the run length distribution for each part of the data with alarm parameters as their variables. Since it is a low alarm limit, P_1 and P_2 are calculated by the following formulas (since the type of the distribution is not known, it is considered as Gaussian distribution):

$$p_1 = 0.5 + 0.5\,erf\,(\frac{L-\mu_n}{\sqrt{2}\sigma_n}) \qquad p_2 = 0.5 - 0.5\,erf\,(\frac{L(1+db)-\mu_n}{\sqrt{2}\sigma_n})$$

For each part of the data P_1 and P_2 are written as a function of the alarm limit and deadband. For example for the first part of the data P_1 and P_2 are as following.

$$p_1 = 0.5 + 0.5\,erf\,(\frac{L - 31.47}{\sqrt{2} * 2.38}) \qquad p_2 = 0.5 - 0.5\,erf\,(\frac{L(1 + db) - 31.47}{\sqrt{2} * 2.38})$$

The run length distribution for each part of the data is obtained by calculating alarm counts corresponding to run lengths up to 1000 seconds. The following formula is used in calculation of alarm counts:

$$AC = n\,(\frac{p_1 p_2}{p_1 + p_2})^2 \times \exp(-\frac{p_1 p_2}{p_1 + p_2} \times x)$$

Here n is the number of data samples, P_1 and P_2 are as explained in the above and x is the run length.

The alarm count of the total data for every run length is obtained by combining all the alarm counts of the different parts of the data together. Chattering is obtained from the final run length distribution as a function of the alarm limit and deadband.

The chattering function can be evaluated for different alarm parameters. In this example, chattering is calculated for alarm limits from 10 to 17 and deadbands from 0 to 0.4. In Figures 4.4 to 4.7 chattering of the total data is plotted versus deadbands considering different thresholds.

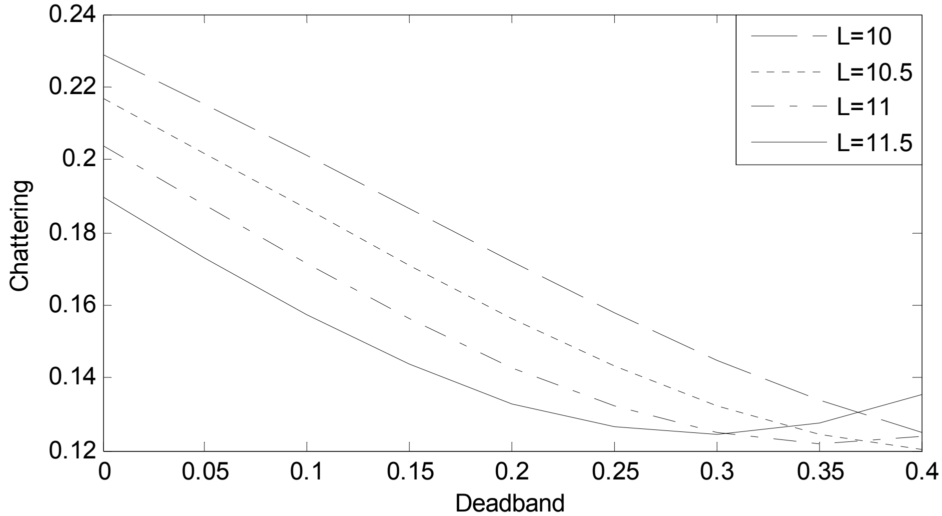


Figure 4.4: Chattering of the data in Figure 4.1 versus deadbands for thresholds from 10 to 11.5

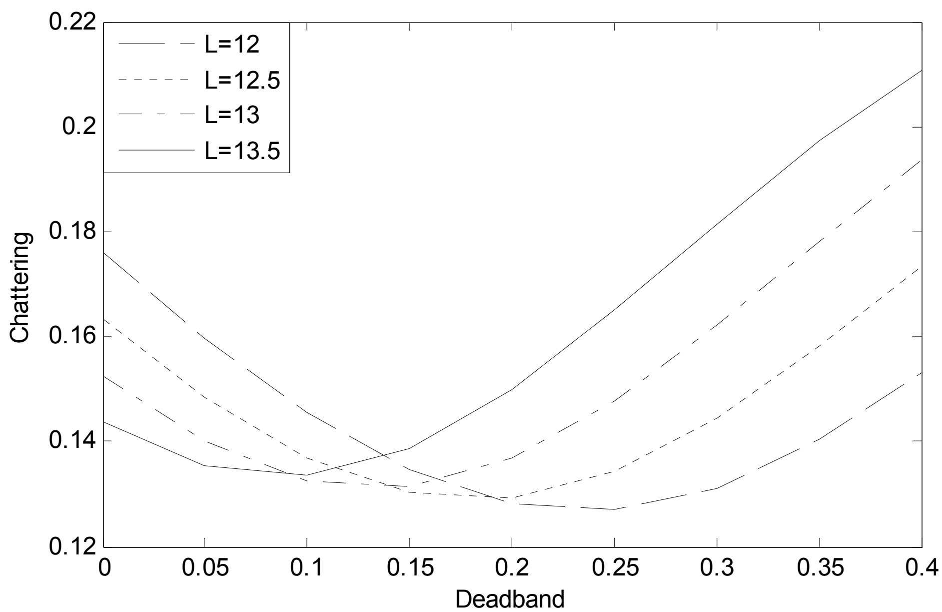


Figure 4.5: Chattering of the data in Figure 4.1 versus deadbands for thresholds from 12 to 13.5

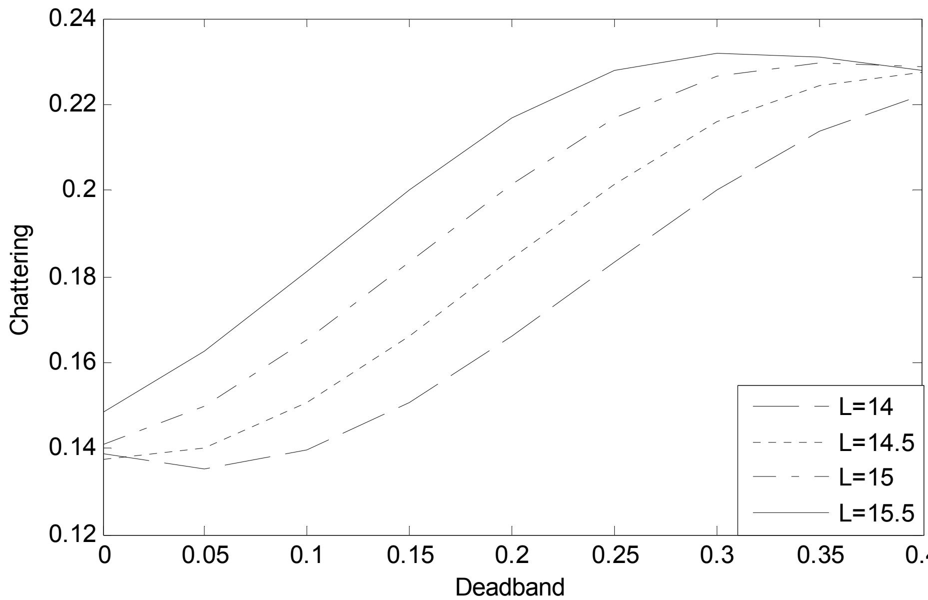


Figure 4.6: Chattering of the data in Figure 4.1 versus deadbands for thresholds from 14 to 15.5

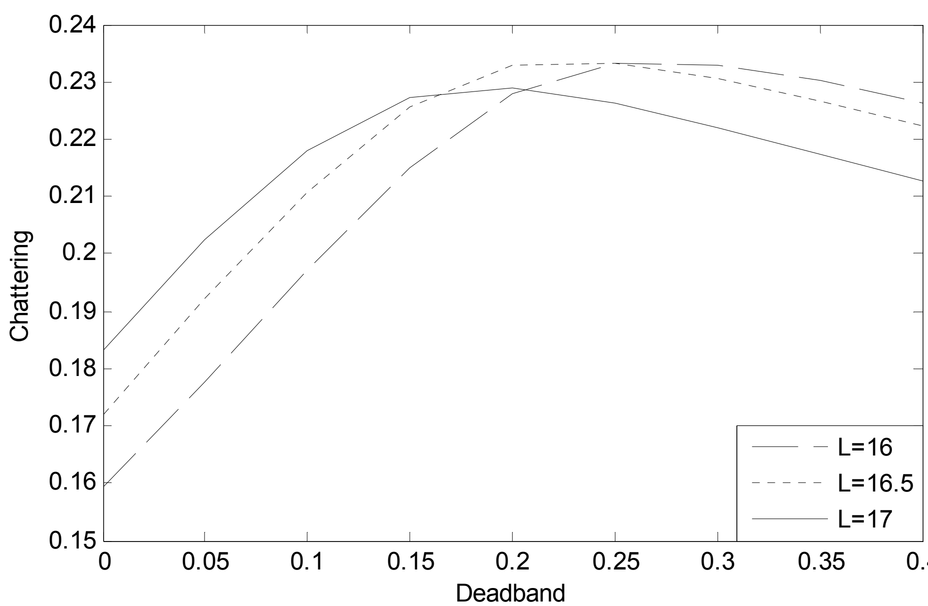


Figure 4.7: Chattering of the data in Figure 4.1 versus deadbands for thresholds from 16 to 17

For lower alarm limits (Figure 4.4) chattering is reduced with increasing the deadband. For higher alarm limits, since the other parts of the data with higher averages also affect the chattering, the behavior of chattering curve changes. If the alarm limit is fixed, measuring the chattering for different deadbands helps in designing the deadband.

In Figures 4.8 and 4.9, chattering is plotted versus alarm limits for different deadbands. Plotting this figure is helpful in cases that the range of the deadband is fixed and the adjusting the alarm limit is considered.

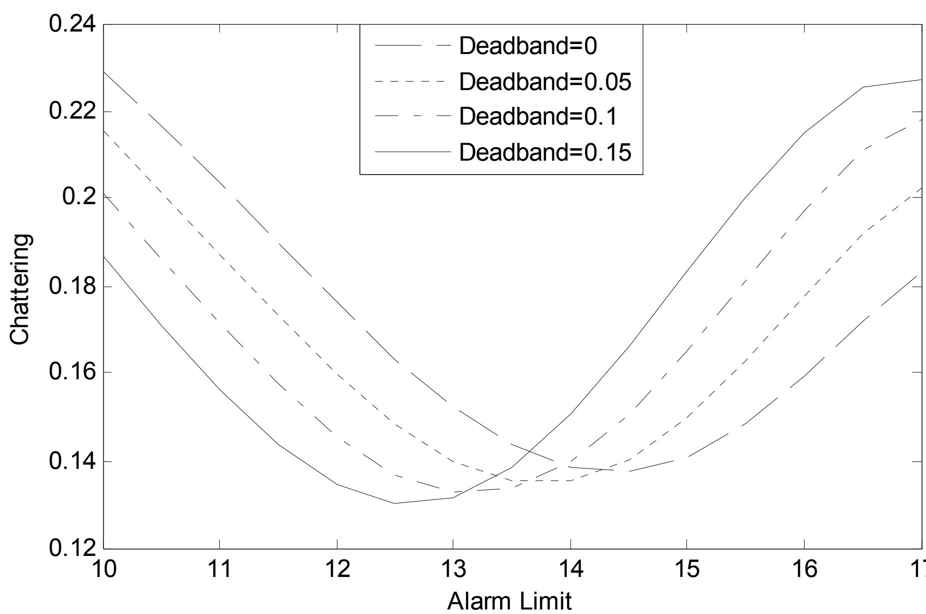


Figure 4.8: Chattering of the data in Figure 4.1 versus alarm limits for deadbands from 0 to 0.15

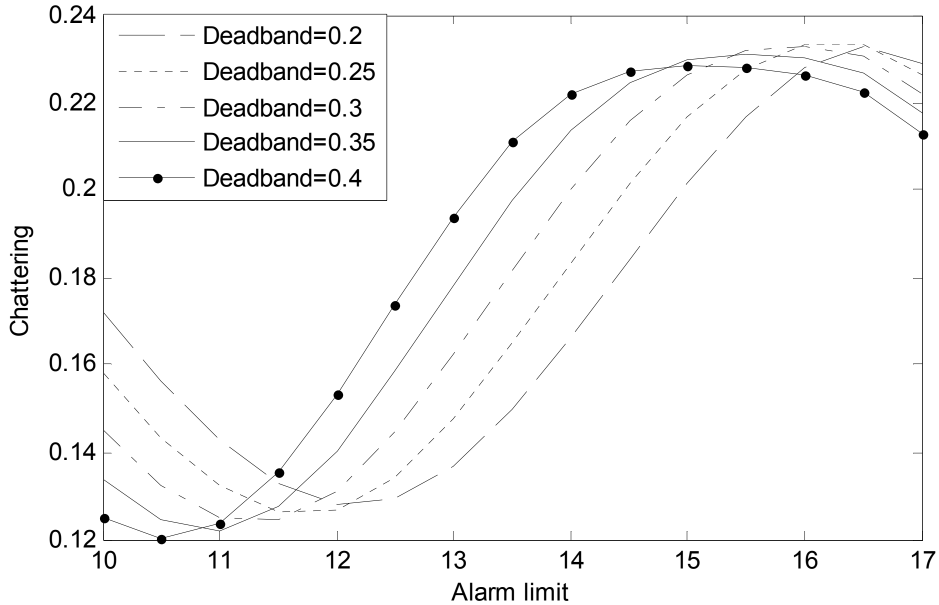


Figure 4.9: Chattering of the data in Figure 4.1 versus alarm limits for deadbands from 0.2 to 0.4

There are two concerns in using these plots in designing the alarm parameters. Since the correlation of the data is not considered in the chattering estimation, the estimated chattering values usually are higher than the real data. For example, the estimated chattering for the case of the original alarm limit and deadband is about 0.12 while its real value is 0.09.

Another important point in using chattering index is that since it is a normalized value, it is not related to the number of alarms. For example, if the data has just two alarms within one second (the time difference between the two alarms is one second), the chattering index equals to 1, which is the maximum chattering. Consider another case in which the data has two alarms within one second and another alarm with two seconds time difference; In this case, the chattering index equals to 0.75 which is less than the previous case. Although it has more alarms compared to the first case but the chattering is significantly lower. So, in the design of the alarm parameters, number of alarms should also be considered along with chattering.

The numbers of alarm counts can also be obtained from the estimated run lengths for the same alarm limits and deadbands as in previous figures. Figures 4.10 and 4.11 depict the estimated number of alarms of the data in Figure 4.1 versus alarm limits considering different deadbands.

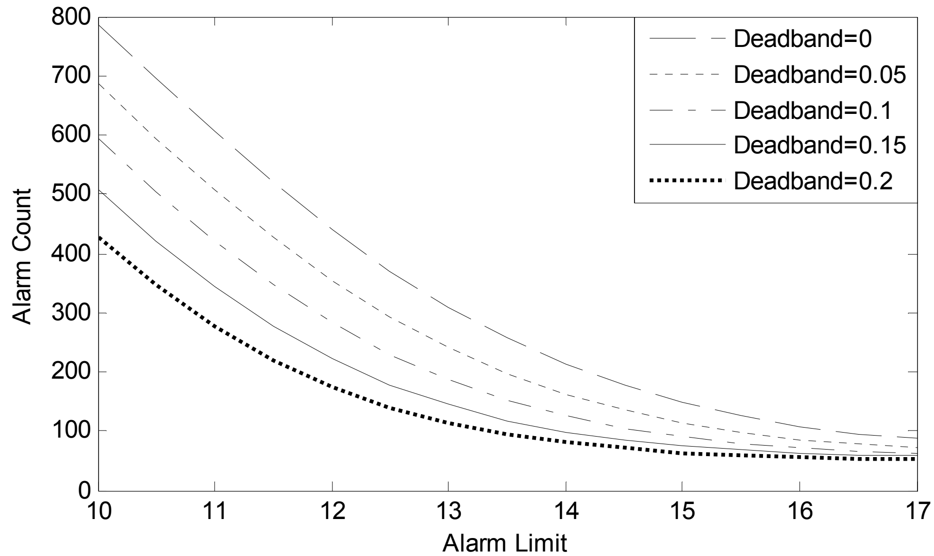


Figure 4.10: Alarm counts of the data in Figure 4.1 versus alarm limits for deadbands from 0 to 0.2

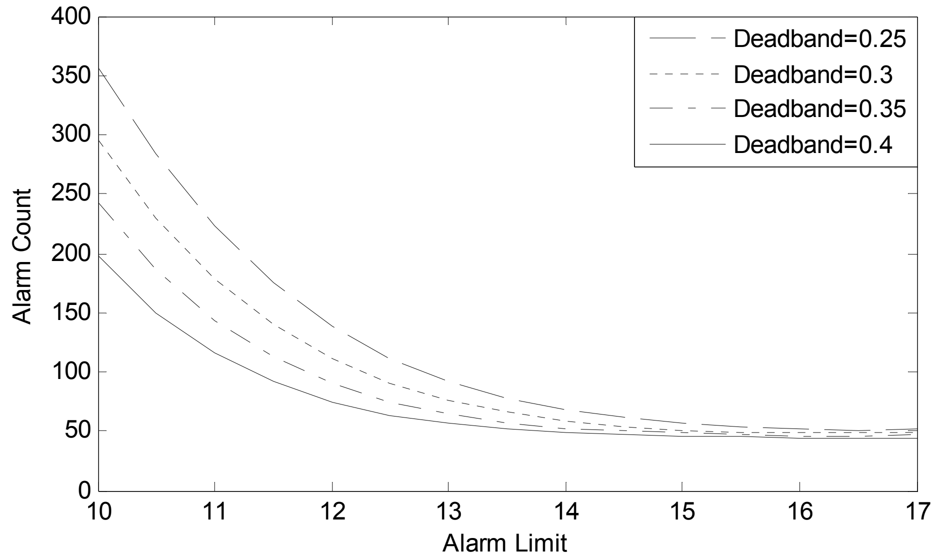


Figure 4.11: Alarm counts of the data in Figure 4.1 versus alarm limits for deadbands from 0.25 to 0.4

From Figures 4.10 and 4.11 it can be seen that increasing the deadband is very effective in reducing the number of alarms for lower alarm limits while it has less effect for higher limits. This fact helps in designing deadband while the alarm limit is fixed. For the alarm limit on 12, increasing the deadband can have a desirable effect on reduction the alarms, but for higher limits it doesn't make much difference.

Presented plots provide a perspective of the effect of the alarm limit and deadband on reduction of the chattering and number of alarms. Also, the limit of effectiveness of increasing the deadband for different alarm limits can be seen from the plots.

Now, the equations presented in Chapter 2 are examined on this industrial tag. Equation (2.8) can be used to obtain the optimal alarm limit for 0.23 deadband. Distribution characteristics of normal and abnormal parts of the data are necessary for this equation.

The normal range of the data is considered as the parts which are higher than the alarm limit. As is seen in Figure 4.1 the data has different distributions in its normal range of operation. However, only the part of the data which is closer to the alarm threshold should be considered in this analysis. For this example, this part is from about 20000 to 60800 seconds. The reason for this choice is that this part is causing the alarms and the alarm parameters should be adjusted to remove the alarms generated by this part of the data.

The abnormal range of operation is also considered as the part which is mostly lower than the alarm limit. For this example, the abnormal part of the data has two parts. One part which has almost constant distribution characteristics is plotted in the last diagram in Figure 4.2. The other part is plotted in the top left diagram of Figure 4.3. As is seen from the figure, the second part has an increasing variance which is much higher than the first abnormal part and also crosses the normal range of the data. Although this part of the data causes most of the alarms, but designing deadbands can’t remove its effect because of its high variance. So only the distribution of the first section of the abnormal part of the data is considered for adjusting the alarm limit.

Using equation (2.14), the optimal alarm limit is obtained as 16.5. This alarm limit with 0.23 deadband generates 47 alarms. As was mentioned in Chapter 2, this equation gives the optimal threshold in terms of least number of false and missed alarms. So the summation of these two alarm rates is plotted for different alarm limits considering the two mentioned normal and abnormal parts of the data. As is seen in Figure 4.12, the summation of false and missed alarm rates is much less in alarm limit 16.5 compared to 12.

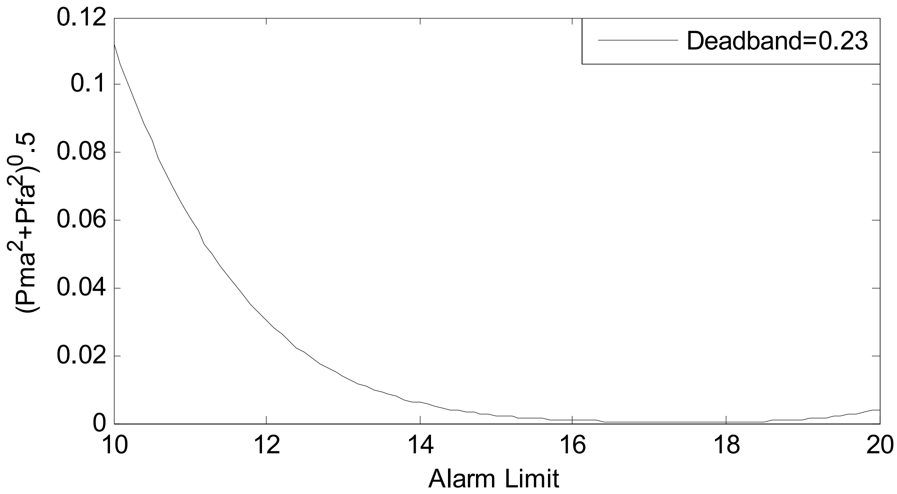


Figure 4.12: Summation of false and missed alarm rates for 0.23 deadband

4.2 Example 2

The next example is another industrial flow measurement from industry. The data which is four day long is plotted in Figure 4.13. The alarm limit on this data is not known, but for the case of discussion it is supposed to be a high alarm. The parts of the data that are higher than almost 25 are considered as abnormal parts of the data and the parts lower than 25 are supposed to be in the normal range of operation.

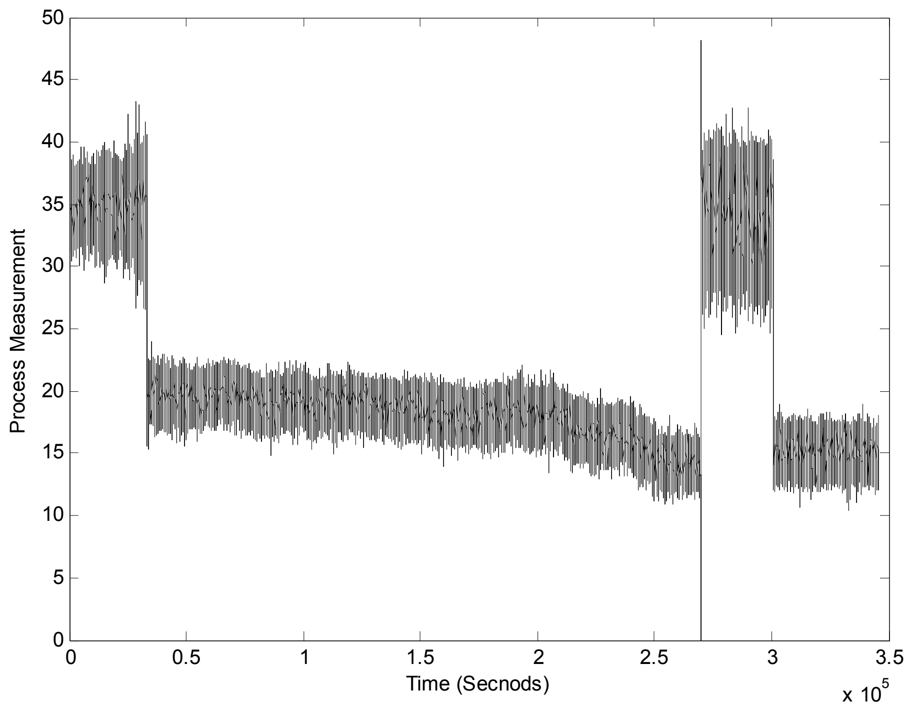


Figure 4.13: Industrial flow measurement with a high alarm limit

The same discussion as in the previous example is done on this data set. Again the data is divided in parts with approximately constant distribution characteristics to be able to get the run length distribution and chattering as a function of alarm parameters. For this purpose, the data is divided in 17 parts as depicted in Figures 4.14 to 4.16. Mean value and standard deviation of each part are noted in the plots.

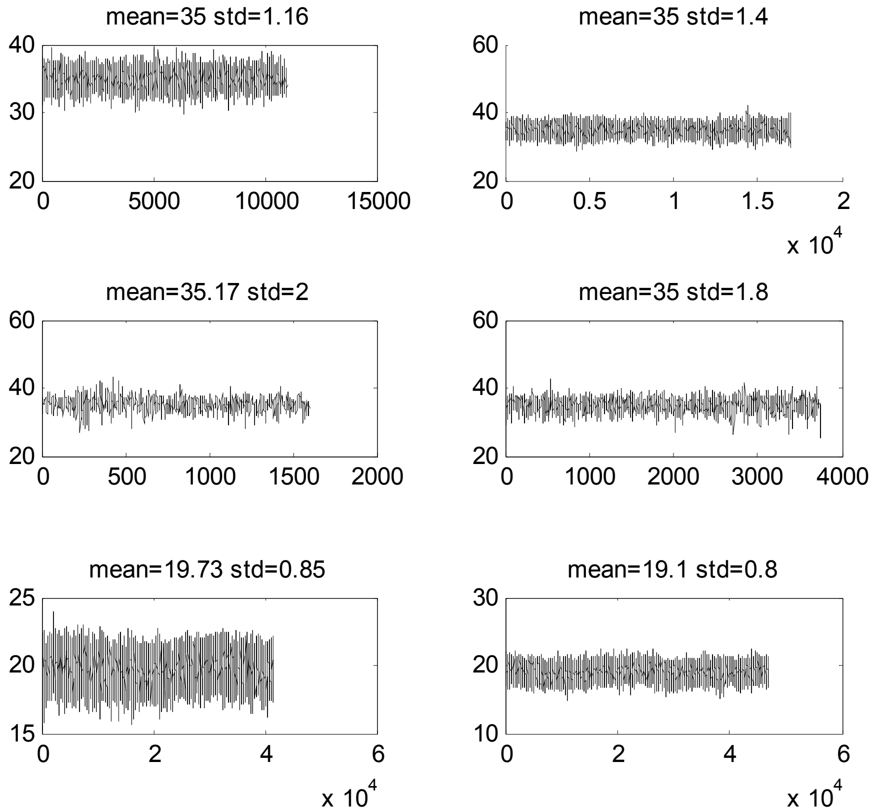


Figure 4.14: Subsections of the data in Figure 4.13

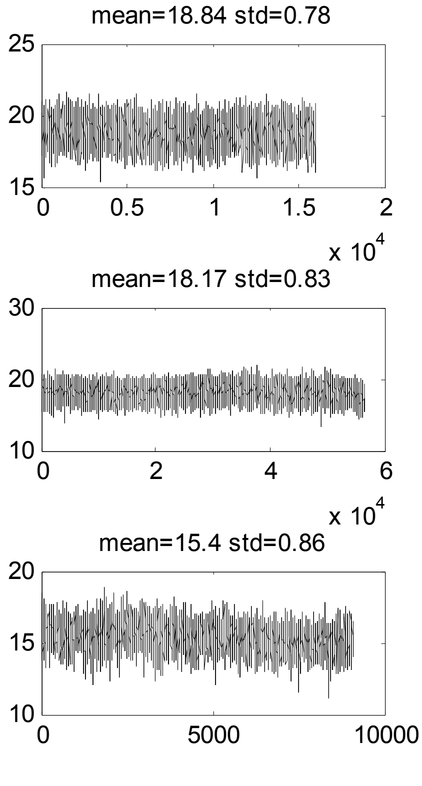


Figure 4.15: Subsections of the data in Figure 4.13

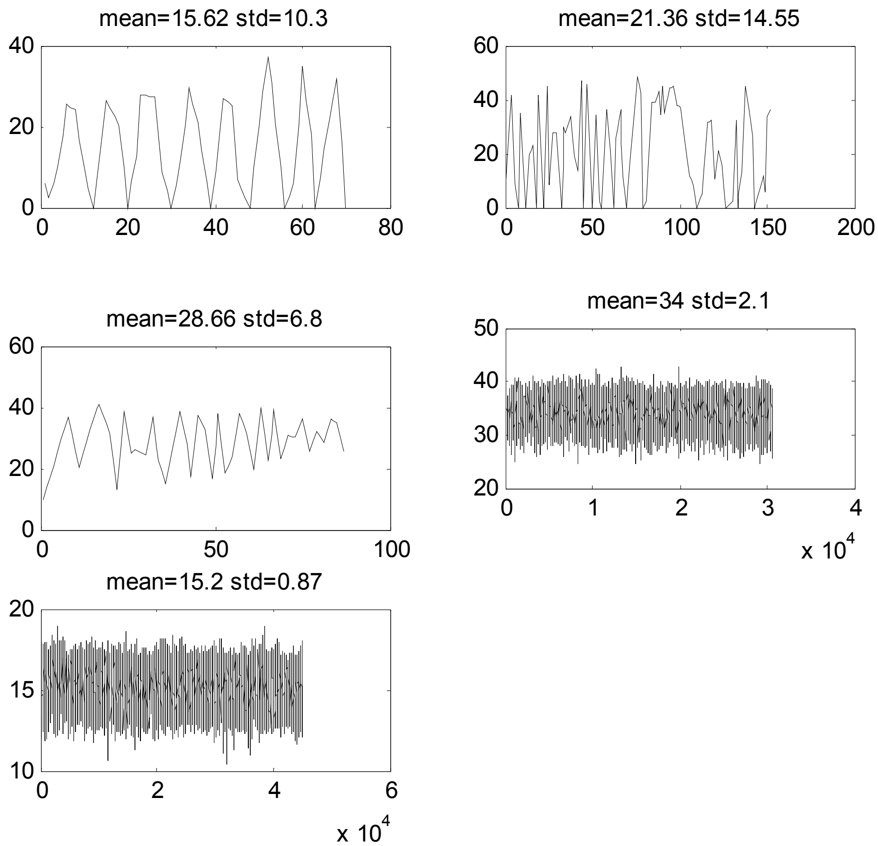


Figure 4.16: Subsections of the data in Figure 4.13

As it is a high alarm, P_1 and P_2 are mathematically written as (assuming Gaussian distribution):

$$p_1 = 0.5 - 0.5 erf(\frac{L - \mu_n}{\sqrt{2}\sigma_n}) \qquad p_2 = 0.5 + 0.5 erf(\frac{L(1-db) - \mu_n}{\sqrt{2}\sigma_n})$$

For each part of the data, P_1 and P_2 should be written with alarm limit and deadband as their variables. The run length distribution of the data is obtained as was discussed in the previous example.

Figures 4.17 to 4.21 depict chattering versus deadbands from 0 to 0.4 for alarm limits from 19 to 30.5. Figures 4.22 and 4.23 plot chattering versus alarm limits for different deadbands. Figures 4.24 and 4.25 plot the alarm counts versus alarm thresholds for different deadbands.

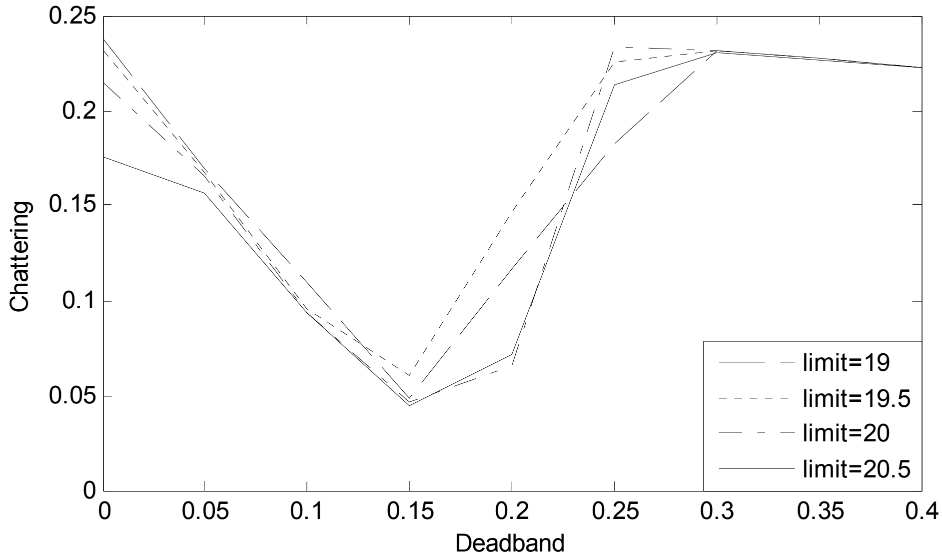


Figure 4.17: Chattering of the data in Figure 4.13 versus deadbands for alarm limits from 19 to 20.5

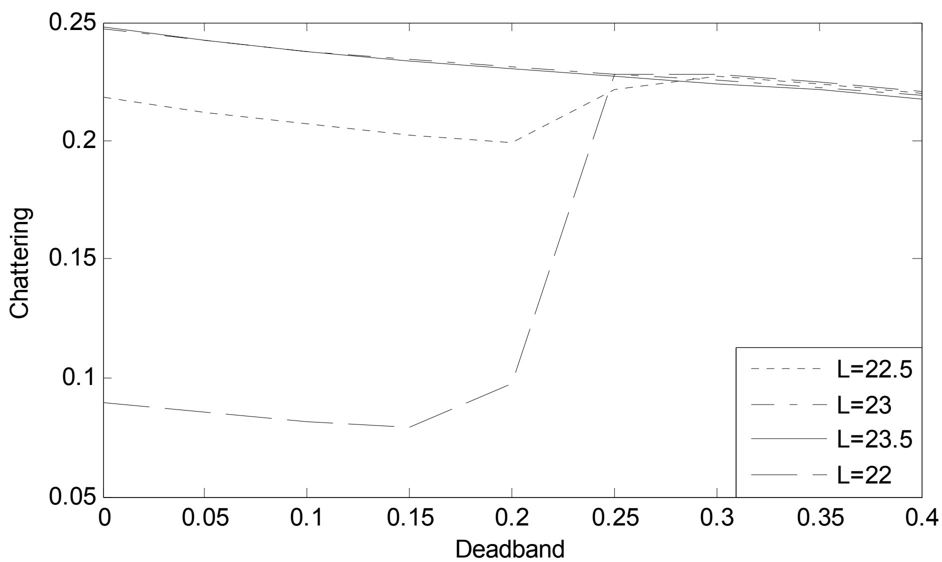


Figure 4.18: Chattering of the data in Figure 4.13 versus deadbands for alarm limits from 22 to 23.5

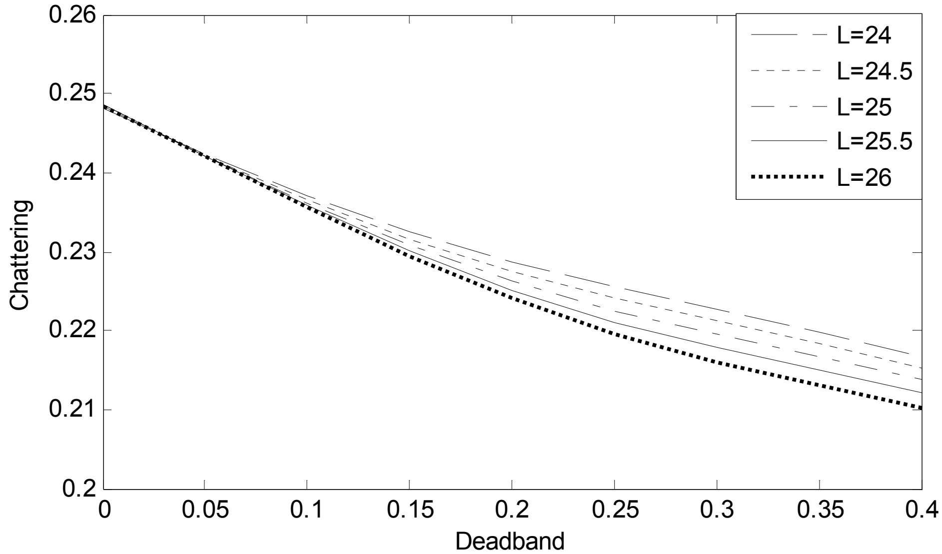


Figure 4.19: Chattering of the data in Figure 4.13 versus deadbands for alarm limits from 24 to 26

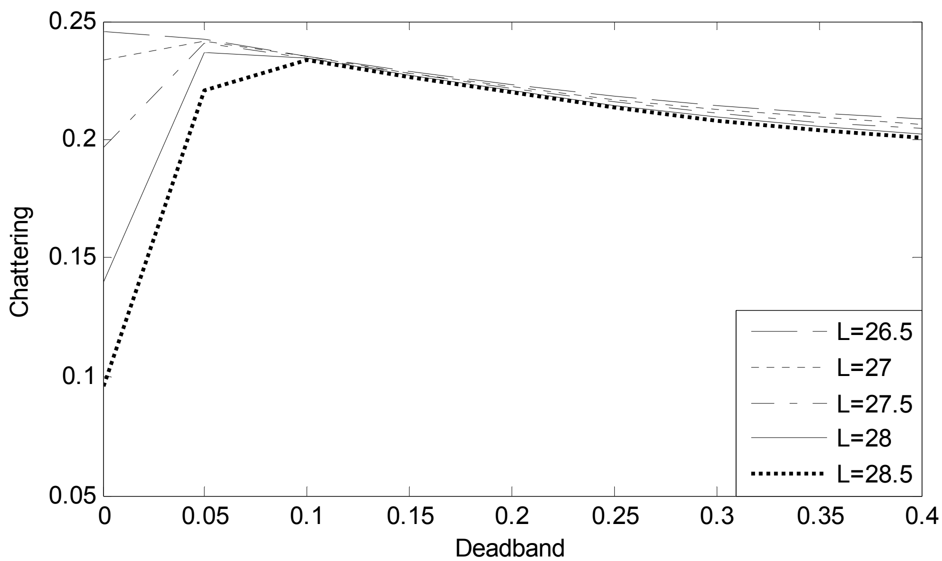


Figure 4.20: Chattering of the data in Figure 4.13 versus deadbands for alarm limits from 26.5 to 28.5

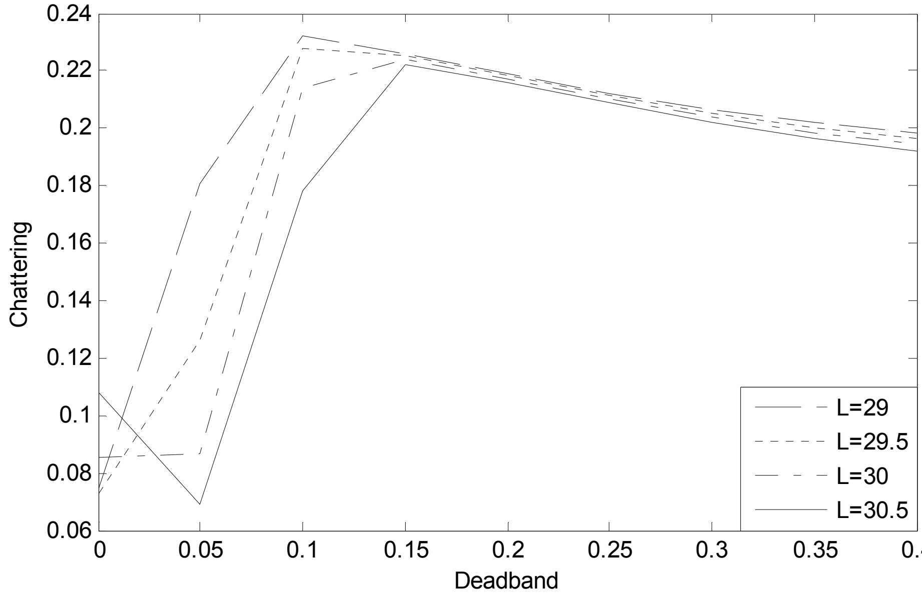


Figure 4.21: Chattering of the data in Figure 4.13 versus deadbands for alarm limits from 29 to 30.5

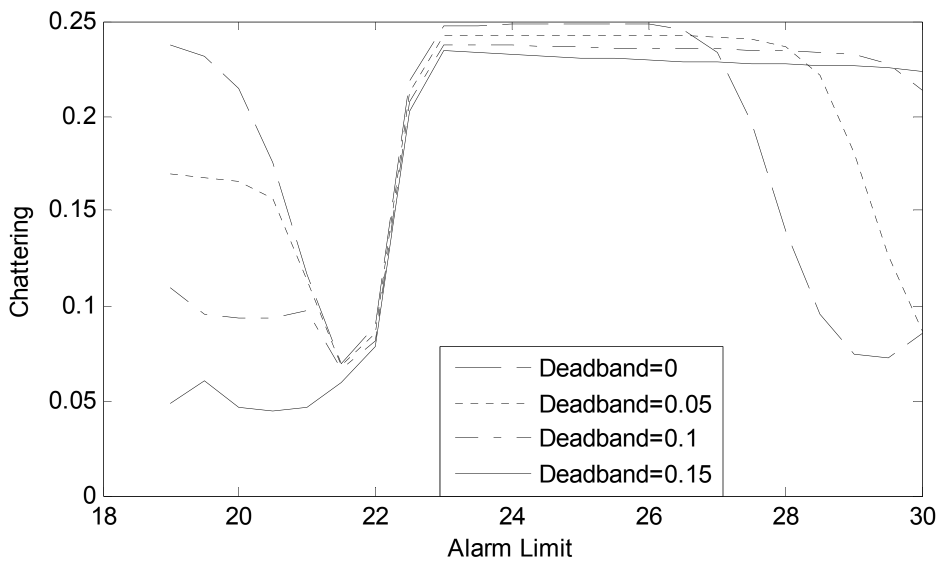


Figure 4.22: Chattering of the data in Figure 4.13 versus alarm limits for deadbands from 0 to 0.15

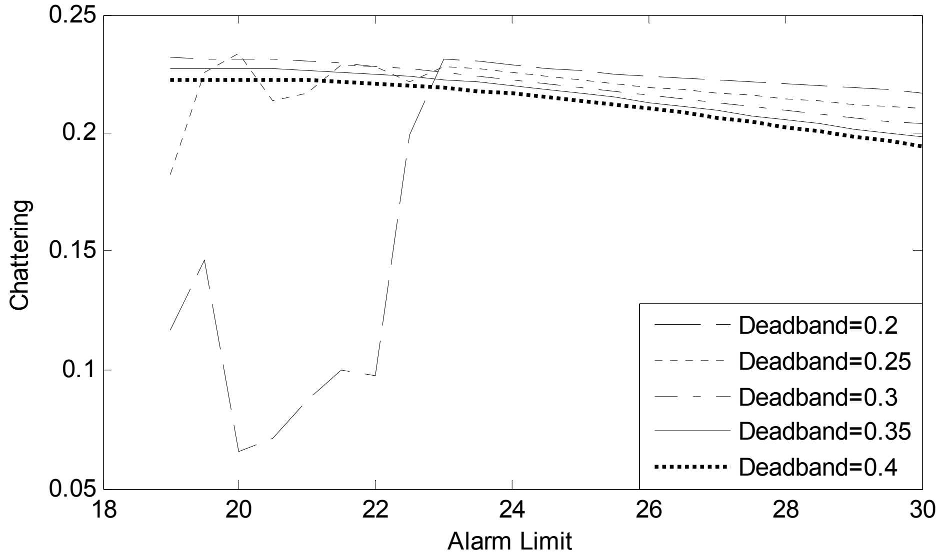


Figure 4.23: Chattering of the data in Figure 4.13 versus alarm limits for deadbands from 0.2 to 0.4

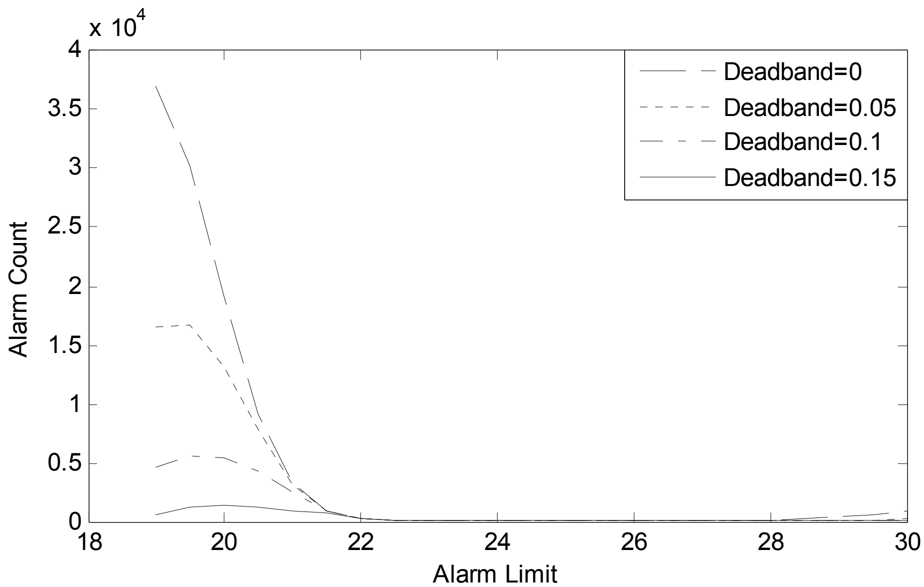


Figure 4.24: Alarm counts of the data in Figure 4.13 versus alarm limits for deadbands from 0 to 0.15

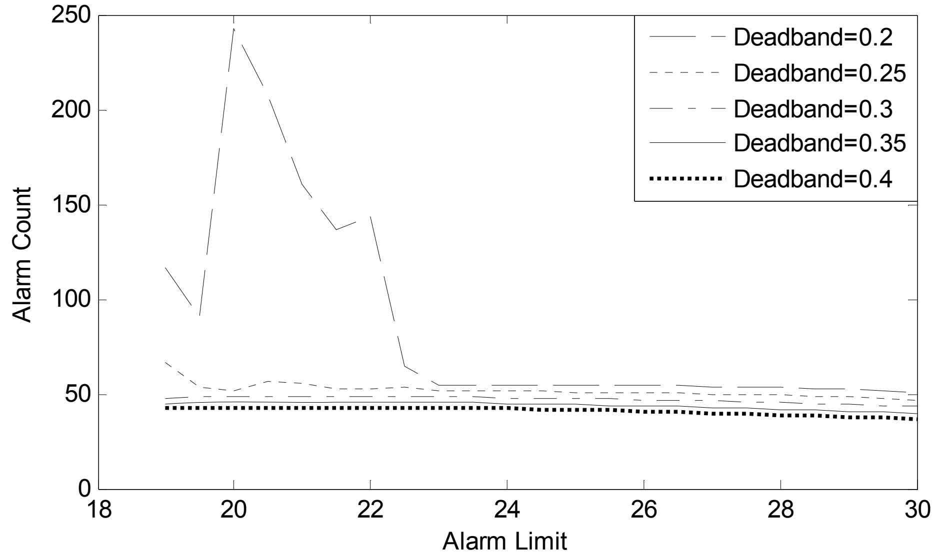


Figure 4.25: Alarm counts of the data in Figure 4.13 versus alarm limits for deadbands from 0.2 to 0.4

From Figures 4.23 and 4.25 it is seen that increasing deadband more than 0.25 is not effective in reduction of chattering or number of alarms for any alarm limit. So the maximum deadband can be taken as 0.2. By considering Figure 4.25 it is seen that the alarm count curve for 0.2 deadband has its lowest value for alarm limits equal or higher than 23.

Although higher deadbands are a little more effective in reducing the number of alarms, but larger deadbands cause more delay in clearing false alarms. Therefore, it is better to choose the minimum acceptable deadband. From the plots 0.2 deadband with alarm limit higher than 23 can be chosen as the range of alarm parameters.

Equation (2.13) is used to get the optimal threshold for 0.2 deadband. Since the two abnormal parts of the data have almost the same averages, the distribution of the abnormal part is estimated from combination of the two parts. For the normal part of the data, only the data between 35000 and 200000 seconds is considered. The reason is that the other parts have less averages and can't be effective in causing chattering.

The optimal alarm limit is estimated by equation (2.13) as 27.5. By mathematically minimizing the summation of false and missed alarms, the optimal threshold is obtained as 26.8. Optimal deadbands obtained by mathematically minimizing the summation of false and missed alarm rates for different thresholds are plotted in Figure 4.26.

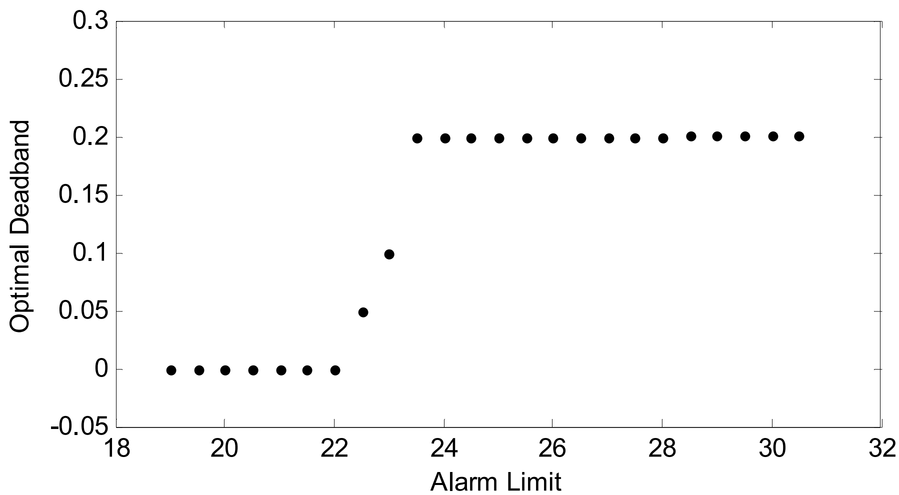


Figure 4.26: Optimal deadbands for different alarm limits

Figure 4.26 confirms the choice of 0.2 deadband as the maximum deadband. As is seen from Figure 4.26 the optimal deadband is 0.1 for alarm limit 23 and is 0.2 for higher limits.

5 Conclusion and future work

This study was divided in two parts. In the first part the relation between alarm limits and deadbands with chattering and false and missed alarm rates was considered. It was shown that the effect of deadband in reduction of chattering or false and missed alarm rates is very sensitive to the alarm limit. Two equations were proposed for estimating the optimal alarm threshold with respect to the deadband from the history of the process data. Also, an equation was derived for calculating the optimal deadband.

In the second part of the study, chattering index was analytically derived as a function of the statistical characteristics of the data and alarm parameters. To use the equations it is necessary to divide the data in parts with constant distribution characteristics and estimate the distribution of each part. A run length distribution should be estimated for each part separately and then by summing all the run length distributions, the distribution of the whole process data is obtained. Chattering is calculated from the total run length distribution. By this method, chattering can be represented as a mathematical function that can be used in the design of alarm parameters. Some examples were presented regarding the usage of the proposed method for alarm design.

The basic idea behind both of the presented topics was that the process data is iid (independently and identically distributed) with known distribution characteristics. As this is not the case in practice, the equations provide estimations of the real values of chattering or optimal deadband and threshold. So, the work can be improved by considering the correlation of the data in the analysis.

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