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A Study on the Relation between Alarm Deadbands and Optimal Alarm Limits*

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***Abstract-* Using alarm deadbands is a common method for reducing the number of false and missed alarms and amount of chattering. Existing methods for designing alarm deadbands are quite general or need online computations. This paper studies the relation between optimal alarm thresholds and deadbands. Two equations are proposed to estimate the optimal threshold with respect to the deadband and history of the process variable.**

I. Introduction

Efficient monitoring of industrial processes directly affects cost reduction and better product quality. This is the reason that fault detection has gained much attention among researchers. There are many modern fault detection methods developed for model based fault detection and also signal based fault detection [1]. Despite this fact, engineers usually use the simplest method, which is comparing the signal with an alarm threshold, for detection of abnormalities in plant operations. In addition to the inappropriateness of this widely used fault detection method, improper design of alarm parameters has worsened the situation of alarm systems.

Receiving an excessive number of alarms per day and even during normal operation of the plants has significantly reduced the usability of alarm systems. Configuring a high number of alarming variables is a primary cause of this problem. In distributed control systems (DCS) adding an alarm is easy; so, there are many redundant alarms configured in every industrial unit.

Receiving many redundant alarms (alarms with no usable information) and chattering alarms (alarms that transit between on and off state before settling [2]) cause too much pressure on the operators. Determining important alarms and the root problem is a hard task when the DCS screen is full of redundant, chattering and false alarms.

Having many alarming variables also makes it hard to perform a proper alarm rationalization practice. As most of the standard methods for alarm rationalization are manual, it takes too much time to rationalize the alarms of any industrial unit. Thus, developing methods for design of alarm parameters that can be automatically used is of great value from the industry perspective.

A common effective method for reduction of alarm chattering is using deadbands. An alarm deadband is defined as “the range through which an input must be varied from the alarm limit necessary to clear the alarm” [2]. Implementing a deadband in the system is in fact determining another limit for clearing the alarm. For example, for a high alarm, the alarm goes on when the variable is higher than the threshold and goes off when the variable is less than threshold-deadband*threshold.

A proper deadband guarantees the least possible amount of chattering. Deadbands have the advantage of being available in many alarm systems. It doesn’t need any memory or special software implementation.

A deadband is usually defined as a percentage of the threshold or the range of the variable. In guidelines a deadband is defined as a percentage of the operating range. In this paper, since we don’t know the range of the variables, “deadband” represents the percentage of the alarm threshold.

There are some recommendations for deadband design in EEMUA [2] and ISA [3] standards. Table 1 show these recommended deadbands based on the type of the process variables. Following these provisions improves the alarm chattering. However, more improvement can be achieved by considering the history of the process variable and fine tuning the deadband or alarm threshold.

Table 1
Standard’s recommendations for alarm deadbands

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

Estimation of alarm deadbands is investigated in [4]. It is proposed to apply time series analysis methods to identify an ARIMA model for the process measurement [5]. The model should be used to predict the future values of the process measurement and its prediction intervals at the time of alarm occurrence. With the knowledge of possible future variable’s trend, a deadband is designed to cover the changes in the measurement due to the noise. Since process variables are very likely to have different structures during different modes of operation, an identification routine should be running on-line. However, it is not likely that industrial operators accept to set a varying deadband. Also, on-line running of the identification procedure requires processor and memory usage. So, an off-line method that estimates the optimal amount of deadband for every process variable with respect to its historical data is preferred.

Another technique for designing deadbands or thresholds which is based on the ROC (Receiver Operating Characteristic) curve is proposed in [6]. A ROC curve is a plot of the probability of missed alarms versus the

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probability of false alarms considering a fixed deadband and different thresholds.

False alarms happen when the process variable is within the normal range, but an alarm is raised for some reason. Missed alarms happen while the variable is out of the normal range but the alarm is off.

It is proposed to plot the ROC curve for different deadbands and then choose the deadband and the corresponding threshold that satisfies some specified limits on the probability of false and missed alarms. Using this method needs some analysis to be done for every variable and it can't be used to estimate the optimal deadband and threshold automatically.

In this paper, the relation between deadbands and alarm thresholds is investigated with respect to statistical characteristics of process variables. Some expressions are derived and verified for estimating the optimal threshold with respect to the deadband. Also, an equation is derived that can be numerically solved for the optimal deadband.

II. Optimality definition

Although qualitative definitions for alarm chattering are provided in standards, they can't be used in deadband design targeting minimum chattering. Having a quantitative definition makes it possible to compare the effectiveness of different deadbands besides defining the optimality condition. The measure that is used hereafter is the chattering index proposed in [7]. This chattering index is based on time differences between successive alarms; the lower the time differences, the higher the chattering. The steps of calculating the chattering index from the alarm database are as follows. First, time differences between successive alarms are measured. The run length distribution of these time differences is constructed by counting the number of repetitions of every specific time difference. For instance, consider the process data in Fig. 1. Simulated data that are used here include one normal and one abnormal part. In Fig. 1, the first half of the data is the normal part and the second half is the abnormal part. The alarm threshold is set at the average of the means of the two parts of data. The run length distribution is plotted in Fig. 2.

In general, run lengths closer to one second have the most contribution to alarm chattering while larger time differences might not be considered chattering at all. To highlight run lengths near one second in the chattering index and attenuate the effect of further time differences, a weighting function is multiplied to the run length. This function is chosen as the inverse of the time difference itself.

The chattering index is then defined as the summation of alarm counts multiplied by the inverse of their corresponding run lengths and divided by the total number of alarm counts. In mathematical format the chatter index is written as $\frac{\sum_r \frac{AC_r}{r}}{\sum_r AC_r}$. Where AC is the abbreviation of alarm count and r is the abbreviation of run length.

The range of this chattering index is from 0% (no chattering) to 100% (reoccurring alarms at every one second).

Using this chattering index, optimal deadbands and thresholds can be defined as the values that generate the least amount of chattering.

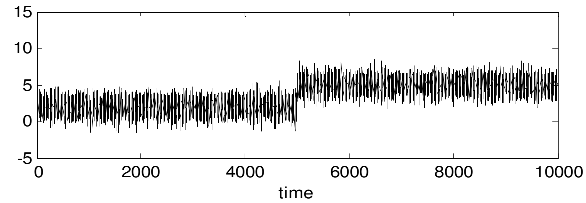

Fig.1. Simulated process data

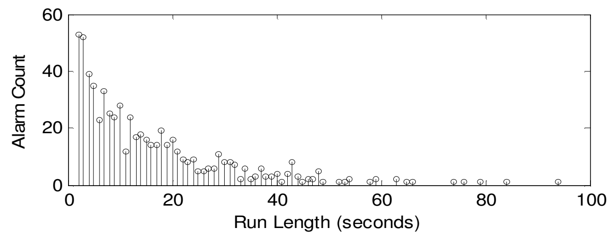

Fig. 2. Run length distribution of simulated data in Fig. 1.

Since reduction of false and missed alarm rates is another important factor in alarm design, another objective can be defined based on the ROC curve. For example the ROC curve for the data shown in Fig. 1 considering zero deadband is plotted in Fig. 3. The ideal point is the origin where the probabilities of false and missed alarms are equal to zero.

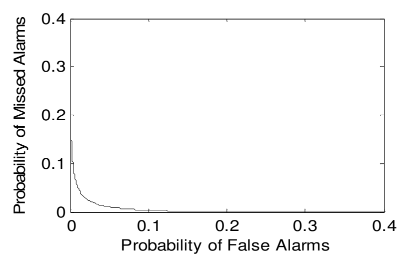

Fig. 3. ROC curve for the data in Fig.1 considering zero deadband

In this work reduction of false and missed alarm rates are assumed to be of equal importance. So, the optimal threshold or deadband are the ones corresponding to the point in the ROC curve which has the minimum distance from the origin. An advantage of choosing this optimality criterion is that the optimal alarm parameters based on this criterion are usually very close to the optimal parameters based on the least number of alarms and chattering. By this definition the optimal deadband or threshold minimizes the summation of squared false and missed alarm rates ($(P_{ma}^2+P_{fa}^2)^{0.5}$). P_{ma} is the probability of missed alarms and P_{fa} is the probability of false alarms.

The method for calculating these probabilities are discussed in [6]. As a brief explanation, suppose having a data set that has Gaussian distributions in its normal and abnormal parts. The probability distribution functions are plotted in Fig. 4. Also consider having a nominal alarm limit "L" and a nominal deadband limit "dbl". If the signal goes beyond the alarm limit there would be an alarm which will be cleared after the signal becomes less than the deadband line.

The probability of false alarms, by applying a Markov chain method, is obtained as $P_{fa} = p_1/(p_1 + p_2)$ [6], where p_1 is the area under the left curve shown in Fig. 4 from the threshold to

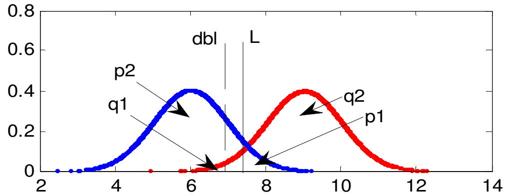

Fig. 4. Distribution of normal (left hand side) and abnormal (right hand side) parts of a simulated data

infinity and p_2 is the area under the same curve from minus infinity to the deadband line. p_1 and p_2 are mathematically written as

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

Here, μ_n and σ_n are the average and standard deviation of the normal part of the data, L is the alarm threshold, db is alarm deadband and *erf*(.) represents the error function ($erf(x) = \frac{2}{\sqrt{\pi}}\int_0^x e^{-t^2}\,dt$).

Probability of missed alarm is calculated by the same procedure considering distribution of abnormal part of the data and is obtained as $P_{ma} = q_1/(q_1 + q_2)$, where q_1, as shown in Fig. 4, is the area under the right curve from minus infinity to the deadband line and q_2 is the area under the same curve from the threshold to infinity. q_1 and q_2 are mathematically written as

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

Where μ_a, σ_a are the average and standard deviation of the abnormal part of the data.

Optimal alarm parameters can be obtained by minimizing the following objective function, which can be done numerically:

$$J(th) = \left(P_{ma}^2 + P_{fa}^2\right)^{0.5} \qquad (1)$$

While the distribution of the data is known, the objective function can be written as a mathematical expression.

III. Effect of Deadband on Chattering Index and Summation of Squared False and Missed Alarm Rates

To investigate the effect of increasing the deadband on the chattering index, many simulations have been done. For instance, a simulated process data is plotted in Fig. 1. The first half of the data, which is the normal part, has Gaussian distribution with a mean of 2 and a standard deviation of 1. The second half of the data, which is the abnormal part, is again Gaussian distributed with a mean of 5 and a standard deviation of 1. Fig. 5 depicts the chattering index for different deadbands. The Alarm threshold is on the average of means of the normal and abnormal parts of the data (3.5 here). As it can be seen in Fig. 5, increasing deadband over 0.2 does not reduce chattering any further. This is almost always true for different data types and different thresholds. When the threshold is fixed, increasing the deadband more than a saturation level will have negligible effect in chattering reduction.

In Fig. 6, chattering is plotted versus different thresholds ranging from 2 to 5 considering different deadbands. Fig. 6 shows that by increasing the deadband, the optimal threshold (corresponding to least chattering) moves slightly toward the mean of the abnormal part of the data. So, to get the least possible chattering, the threshold should change according to a change in the deadband.

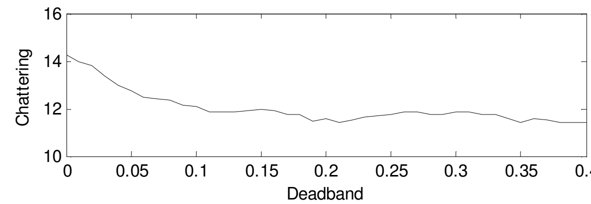

Fig. 5. Chattering versus deadband

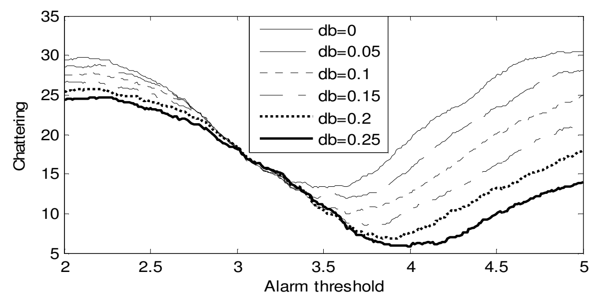

Fig. 6. Chattering versus alarm thresholds for different deadbands (for simulated data in Fig. 1.)

Another similar simulation is performed on the same data that calculates $(P_{ma}^2+P_{fa}^2)^{0.5}$ for the same deadbands and same threshold range. The result is plotted in Fig. 7. The movement of the optimal threshold to abnormal part of data is also seen in this figure. By comparing Fig. 6 and 7 it is observed that optimal thresholds based on chattering and least summation of squared false and missed alarm rates are approximately equal.

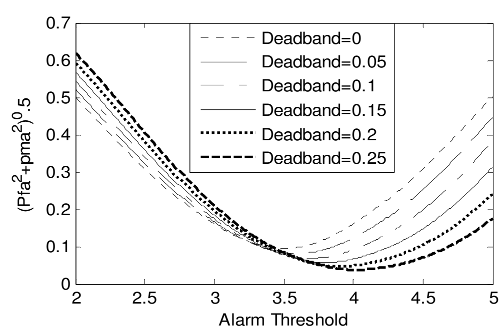

Fig. 7. $(P_{ma}^2+P_{fa}^2)^{0.5}$ versus alarm thresholds for different deadbands (for simulated data in Fig. 1.)

Same simulations have been done for another data set which is plotted in Fig. 8. The normal part of the data again has a mean value of 2 and a standard deviation of 1 while the mean value of the abnormal part is 5 with a standard deviation of 2. Fig. 9 plots chattering versus thresholds for the same deadbands as in Fig. 6.

By comparing Fig. 6 and 9, it can be seen that when the standard deviation of the abnormal data is larger, movement of the optimal threshold toward the mean value of the abnormal part of the data is slower.

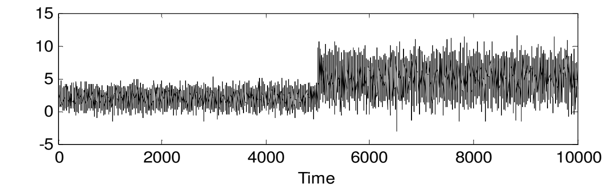

Fig. 8. Simulated process data

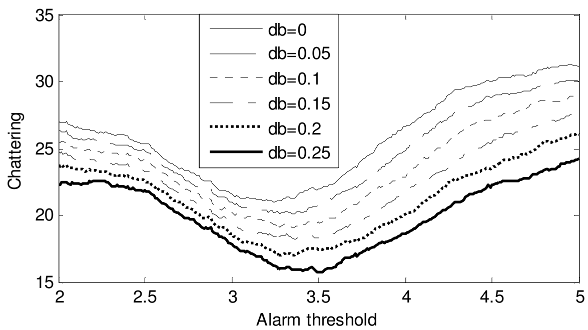

Fig. 9. Chattering versus thresholds for different deadbands (for simulated data in Fig. 8)

IV. Estimation of optimal alarm threshold

As was shown, the optimal threshold changes for different deadbands. So, it is necessary to adjust the threshold with respect to deadband in the design of alarm parameters. Here, it is tried to find the optimal threshold with respect to deadband and statistical characteristics of process data. First the case of zero deadband is considered.

As the optimal threshold is assumed to be the threshold which minimizes the summation of squared false and missed alarm rates, the derivative of the summation should be zero at the optimal threshold. So, the following equation can be solved to obtain the optimal threshold:

$$\frac{d(p_{fa}^2 + p_{ma}^2)}{dL} = 0 \rightarrow \frac{d\, p_{fa}^2}{dL} + \frac{d\, p_{ma}^2}{dL} = 0 \qquad (2)$$

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) simplifies to

$$2p_1 \frac{d\, p_1}{d\, L} + 2q_1 \frac{d\, q_1}{d\, L} = 0 \qquad (3)$$

By assuming Gaussian distributions for the data,

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

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

Substituting the mathematical expressions of p_1 and q_1 and their derivatives, equation (3) becomes

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

As the equation can't be analytically solved for the optimal threshold, an approximation is being used. For zero deadband the ROC curve is usually symmetric. So, the threshold corresponding to the minimum distance from the origin is very close to the threshold where the false and missed alarm rates become equal. Thus, the solution for p_1=q_1 can be used to approximate the solution of equation (3). The solution of p_1=q_1 is

$$L = \frac{\mu_n \times \sigma_a + \mu_a \times \sigma_n}{\sigma_n + \sigma_a} \qquad (4)$$

This structure is considered in the curve fitting procedure to find the best estimation of 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. The equation obtained for the high alarm case is

$$L = \frac{\mu_n \times \sigma_a + \mu_a \times \sigma_n}{1.2\sigma_n + 0.8\sigma_a} \qquad (5)$$

and the equation for the low alarm is

$$L = \frac{\mu_n \times \sigma_a + \mu_a \times \sigma_n}{0.95\sigma_n + 1.13\sigma_a} \qquad (6)$$

For the case of nonzero deadbands analytical approach doesn't generate any results even by considering approximations. For example, by substituting the error function in P_{ma}=P_{fa}, with its Taylor series approximation, a very lengthy quadratic equation for the optimal threshold is obtained. Because of the complexity of the coefficients, it can't be solved for the threshold. So, curve fitting methods are used to find an equation in order to estimate the optimal threshold.

About 150,000 data sets with different statistical characteristics and different deadbands were generated. The optimal threshold is obtained for each case by mathematically minimizing the summation of squared false and missed alarm rates. Nonlinear regression is used to estimate the parameters of the optimal threshold function. The structure of the function is inferred from the structure of equation (4) and the facts inferred from earlier simulation examples.

As was mentioned, by increasing the deadband the optimal threshold moves toward the abnormal part of the data and its movement is slowed by increasing the standard deviation of the abnormal part of the data. So, some weight proper to the deadband should be given to the mean value of the abnormal part in equation (4) and smaller weight to its standard deviation in the denominator. The structure of the function for modeling is considered as

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

where $\alpha_1 - \alpha_7$ are parameters to be estimated.

For the high alarm case the equation is obtained as

$$optimal\ L = \frac{\mu_n \sigma_a + (1+db)\mu_a \sigma_n}{1.2\sigma_n + (0.8 + 0.27\, db)\sigma_a} \quad (7)$$

In Fig. 10 the optimal thresholds obtained by estimation are plotted versus the optimal thresholds obtained by mathematical optimization.

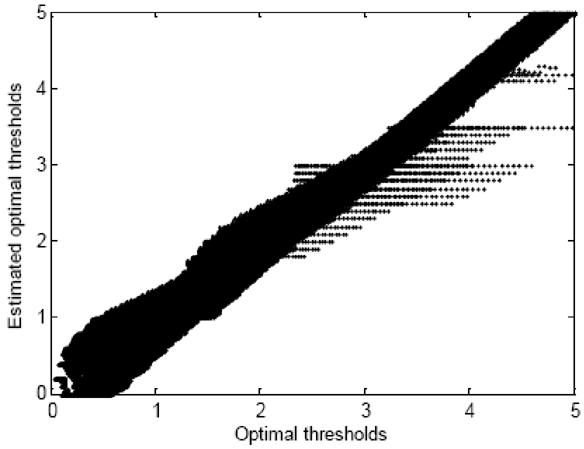

Fig. 10. Estimated optimal thresholds by equation (7) versus the optimal thresholds obtained by mathematical optimization

By fitting a linear model between optimal thresholds and estimated ones, their relation is obtained as

L=0.995*ESTL+0.000

Where L is the real optimal threshold and ESTL is the estimated one.

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

$$optimal\ L = \frac{\mu_n \sigma_a + (1+db)\mu_a \sigma_n}{0.95\sigma_n + (1.13 + 1.08\, db) \times \sigma_a} \quad (8)$$

Fig. 11 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.

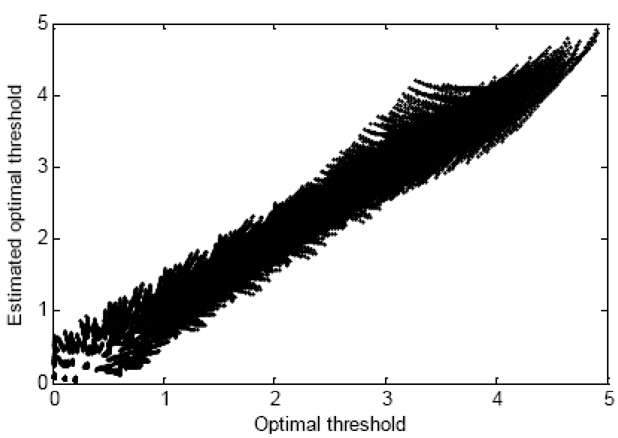

Fig. 11. Estimated optimal thresholds by equation (8) versus the optimal thresholds obtained by mathematical optimization

To see the closeness of estimated optimal thresholds to the optimal thresholds based on chattering, some simulation results are shown here. The statistical characteristics of the process data sets used in simulation are listed in Table 2.

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 least summation of squared false and missed alarm rates are obtained in the simulations. The results are depicted in Fig. 12 and 13. Fig. 12 plots the estimated optimal thresholds versus the optimal threshold obtained by mathematical optimization of $(P_{ma}^2+P_{fa}^2)^{0.5}$. Fig. 13 depicts the estimated thresholds versus the thresholds based on the least chattering.

Table 2
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

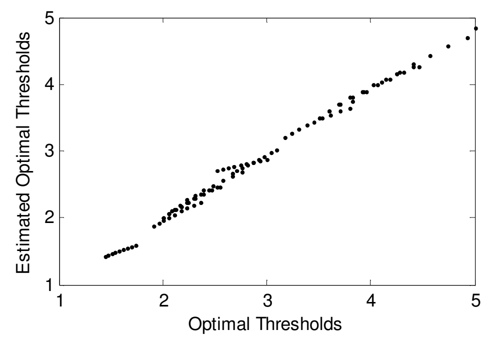

Fig. 12. Estimated optimal thresholds versus the optimal thresholds obtained by optimization

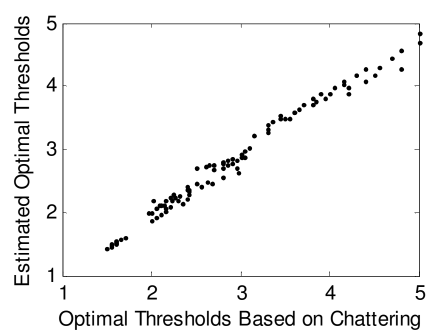

Fig. 13. Estimated optimal thresholds versus the optimal thresholds based on chattering

From Fig. 12 and 13 it is inferred 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 both definitions.

V. Relation Between Optimal Deadband with Data Characteristics and Alarm Threshold

Here the optimal deadband is considered as the one that minimizes the summation of squared false and missed alarm rates. To see how the optimal deadband varies with respect to the alarm threshold, the result of a simulation is shown in Fig. 14. The simulated data set is plotted in Fig. 1. The alarm threshold is moving from the mean value of the normal part of the data to mean value of its abnormal part. For each threshold, the optimal deadband is mathematically obtained by minimizing $(P_{ma}^2+P_{fa}^2)^{0.5}$. The maximum value of deadbands is determined as 0.5.

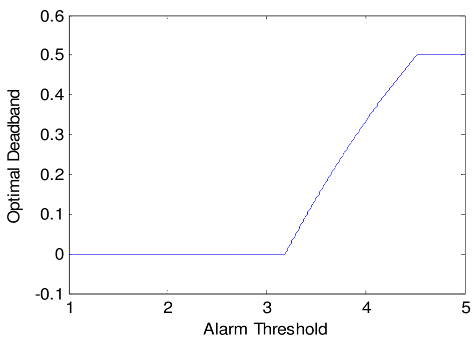

Fig. 14. Optimal deadband versus the alarm thresholds for data in Fig.1

From Fig. 14 it is seen that the optimal deadband starts increasing from zero when the threshold is at 3.2, which is less than the average of mean values of normal and abnormal parts of the data (3.5), and then has a linear relationship with threshold until it hits its maximum value.

It is tried to analytically find the relation between optimal deadbands and thresholds. The derivative of $(P_{ma}^2+P_{fa}^2)^{0.5}$ with respect to the deadband should be zero at the optimal deadband. So,

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

$$-2p_1^2(q_1+q_2)^3\frac{d(p_2)}{d(db)} + 2q_1q_2(p_1+p_2)^3\frac{d(q_1)}{d(db)} = 0 \qquad (9)$$

where

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

By replacing p_1, q_1, p_2, q_2 and their derivatives with respect to the deadband in equation (9), a complicated equation is obtained that is highly nonlinear with respect to the deadband. The equation can not be solved analytically for the optimal deadband; but if the statistical characteristics of the data are known the equation can be numerically solved to obtain the optimal deadband.

V. Discussions and Case Study

For both low and high alarms if the difference between mean values of normal and abnormal parts of data is equal to or more than three times the sum of their standard deviations, even zero deadband generates small chattering. The presented simulated data sets were chosen to cover the cases with little distance between the mean values of normal and abnormal parts of data. It was seen that the equations are making acceptable estimations of the optimal thresholds. So, by using the equations, it is possible to minimize chattering and probability of false and missed alarms together.

Even though the results of only Gaussian distributed data sets were presented in the paper, but the equations work with low errors when testing by data sets having other kinds of distributions.

To verify the proposed expressions in practice, an industrial data set is considered. The data set, which is a flow measurement, is plotted in Fig. 13. The original low alarm threshold is set at 12 and the deadband width is 2.75 (which implies deadband line on 14.75). It generates 75 low alarms in one hour and the summation of squared false and missed alarm is 0.024.

By using equation (8), the optimal threshold for this deadband is obtained as 16.7. By adjusting the alarm threshold with the same deadband, the number of alarms reduces to 37 and the summation of false and missed alarm rates reduces to 0.0002.

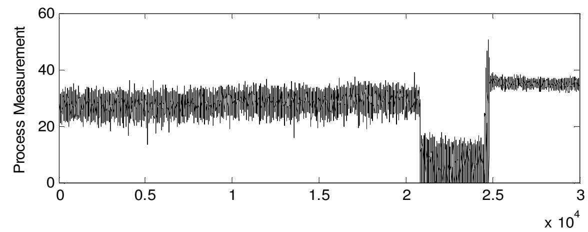

Fig. 16. Industrial flow measurement.

VII. Conclusion

In this paper the relation between deadbands and alarm thresholds was studied. It was shown that increasing the deadband for a fixed threshold is not very effective in reducing chattering and a better approach is to adjust the threshold according to the deadband. Two expressions were proposed to estimate the optimal threshold with respect to the deadband and statistical properties of the process variable.

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