An Optimization-based Method to Define Dead-band Values of Industrial Alarms ⋆

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Abstract: Industrial alarms are a way to maintain a proper and secure operation of industrial processes avoiding productive and quality losses, accidents, and possible environmental disasters. However, most alarm systems suffer from the high incidence of chattering alarms, which are alarms that rapidly transit from active and inactive states. To minimize this problem, alarm systems use dead-band techniques to alarm thresholds. However, the alarm dead-band parameters must be well tuned to be effective. In this context, this work proposes a method to improve the quality in specifying alarm dead-bands. The method is based on optimization of performance metrics of alarm systems considering the actual alarm threshold. This method provides effective alarm dead-band values that reduce chattering alarms without being excessively large. To validate our approach, a case study was used to determine the efficiency of the proposed method in comparison with common standards. The data for the case study was generated using Tennessee Eastman Process, which is a well-known simulator in literature.

Keywords: Alarm systems; alarm Dead-band; Parameter optimization.

1. INTRODUCTION

According to ANSI/ISA (2009), an alarm is defined as "an audible and/or visible means of indicating to the operator an equipment malfunction, process deviation or abnormal condition requiring a timely response". Thus, industrial alarms have an important role in industrial process monitoring and they must be properly configured in order to avoid minors and majors problems since the lost of production to possible environmental disasters.

Usually, industrial alarms are implemented as thresholds that delimit safe operational regions for relevant process variables. Thus, when a monitored process variable goes out of its safety operational region the respective alarm is raised. On the other hand, when the process variable returns to its normal operational region the alarm is cleared.

This approach generates nuisance alarms caused by noise or poor configuration for its simplicity. Chattering alarms are an example of nuisance alarms that rapidly transit from and to the safety region [ANSI/ISA, 2009]. Chattering alarms are one of the principal causes of alarm overloading, accounting for up to 70% of the alarm occurrences [Wang et al., 2016]. This problem has motivated the creation of metrics for chattering alarms, such as the chattering index [Kondaveeti et al., 2013]. Alarm chattering causes indirect and direct effects such as the cry-wolf effect and increases alarm occurrences to a level that industrial operators can not handle.

In order to reduce the chattering alarms, it is common to use alarm dead-band strategy. The alarm dead-band strategy defines a region that the process variable must pass through in order to clear. The chattering alarms are reduced using alarm dead-bands by creating an additional barrier for an alarm state to change.

Some approaches have been proposed in literature to set-up the dead-band parameter of industrial alarms. For example, in Hugo (2009) was proposed an online approach based on time series analysis to determinate the alarm dead-band value. This approach makes a prevision of the future behavior of process variable based on the past data at the moment of the alarm raising and uses the confidence interval for set an alarm dead-band. Intuitively, this approach creates an alarm dead-band that if the process keeps the trend it has before the alarm raising it will not transit to clear state. The drawbacks of that approach are online complex computations and a resistance from industry for implement a varying alarm dead-band strategy.

Tulsyan and Gopaluni (2019)

An optimization approach based on ROC curves for optimal design of alarm system was proposed in Izadi et al. (2009). More specifically, the alarm dead-band value that

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minimizes the chattering index is obtained by optimizing performance using ROC curves [Naghoosi et al., 2011]. It is possible to use kernel density estimation to perform the optimization process using process variable data and adjusting the alarm parameters Hao and Hongguang (2014). Recent works expanded the framework to consider more variables and implement a multi variable optimization using correlation measures from process variables Han et al. (2016). This optimization framework also enables the optimization of multiple alarm parameters at a time, *e.g.*, defining a triggering threshold and a clear threshold Tulsyan and Gopaluni (2019). However, alarm dead-band values obtained by optimization can produce regions of dead-band excessively large, which can produce long standing alarms or even make impossible to the alarm to clear. To prevent these kind of inadequate effects it is necessary to delimit in optimization process the maximum acceptable range for the alarm dead-band. Thus, on the one hand, alarm dead-band techniques reduce the effects of alarm chattering, on the other hand they can cause problems in the activation and deactivation time of alarms.

Aware of this problem, we propose an optimization-based method to define alarm dead-band values to remove chattering alarms and to avoid impacting on activation and deactivation alarm times. In our proposal, the alarm threshold is kept fixed during optimization considering the critical importance to assure safety. Then, a split on the process data is made using the threshold to avoid creation of excessively large alarm dead-band values.

In order to evaluate the feasibility of the our method, its performance is compared to alarm dead-bands values obtained using the ANSI/ISA standards [ANSI/ISA, 2009] with respect to the ability to reduce chattering alarms without impact on activation and deactivation alarm times.Also, our method is easily applied to different alarm dead-bands standards such as EEMUA [EEMUA, 2007].

The rest of the paper is organized as follows. In Section 2 the alarm dead-band definitions are presented. The proposed method is detailed in Section 3. Aiming to validate the proposed approach, a case study is carried-out in Section 4. Finally, in Section 5 the conclusion and some comments are presented.

2. ALARM DEFINITIONS

Industrial alarms are an important safety tool for industrial process. It is used to report dangerous behavior of the process to the operator. Then the operator have to take a corrective action in order to clear the alarm. Formally, an alarm can be described as a binary signal where 1 represents the alarm state and 0 represents cleared or inactive alarm state. This signal is generated based on the process variable and the alarm parameters. The simplest alarm configuration given a process variable is to define by an alarm threshold. Considering an alarm of the type high, if the process variable is above the value of the alarm threshold then an alarm is raised. Equation 1 describes an alarm signal, x_a, for a process variable, x, with alarm threshold, x_{tp}.

$$x_a(t) = \begin{cases} 1, & x(t) > x_{tp} \\ 0, & x(t) \leq x_{tp} \end{cases} \tag{1}$$

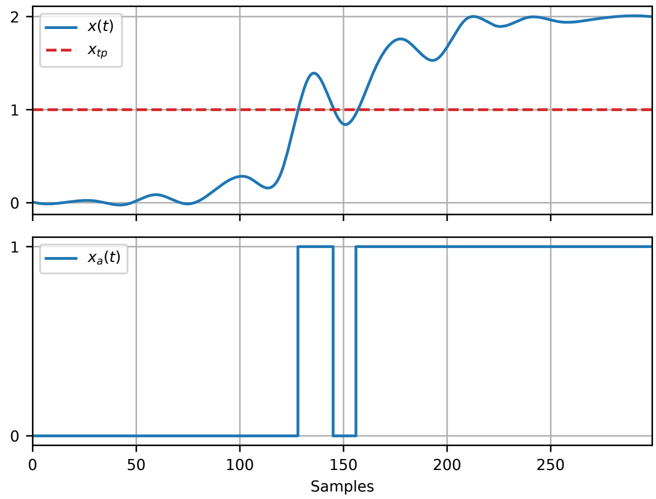

Figure 1. Example of alarm generated with alarm threshold.

It is possible to notice in Figure 1 that the alarm clears, $x_a(t)$, even the process, $x(t)$, clearly staying in abnormal state. This event is known as missed alarm. For the process data present in Figure 1 it is possible to define an alarm threshold that will not produce missed alarms. Which would not be the case with a noisy process data.

To avoid the missing alarms it is needed to provide a difficulty for the alarm to clear. In this context an alarm dead-band is set. The alarm dead-band is a region which the process variable must pass through in order to change the state. The region may be defined from the alarm towards normal operation [ANSI/ISA, 2009] or expanded around the alarm threshold [EEMUA, 2007]. Equation 2 defines an alarm signal, x_a, from a process variable, x, using an alarm threshold, x_{tp}, and an alarm dead-band with a clear threshold, x_{db}, according to ISA 18.2 standard for a high alarm.

$$x_a(t) = \begin{cases} 1, & x(t) > x_{tp} \\ 0, & x(t) < x_{db} \\ x_a(t^-), & x_{db} \leq x(t) \leq x_{tp} \end{cases} \tag{2}$$

where t^- means previous time instant.

Using the same example from Figure 1 with addition of an alarm dead-band it is possible to remove the missed alarm (Fig. 2). In this case the alarm dead-band was set from the alarm threshold, x_{tp}, towards the normal region producing a clear threshold, x_{db}.

Application of alarm dead-bands for reducing alarm chattering is a well-known method in the industry and present in international standards, e.g. ANSI/ISA. Table 1 lists the recommended starting points by signal type for alarm dead-band presented by ANSI/ISA's alarm management standard. The percentage in Table 1 is related to the operating range of given process variable.

When defining alarm dead-band it is important to guarantee that the addition of this clearing barrier does not create an alarm that stills active for long periods, known as stale alarms [ANSI/ISA, 2009]. The occurrence of stale alarms can be caused by excessively larges alarm dead-

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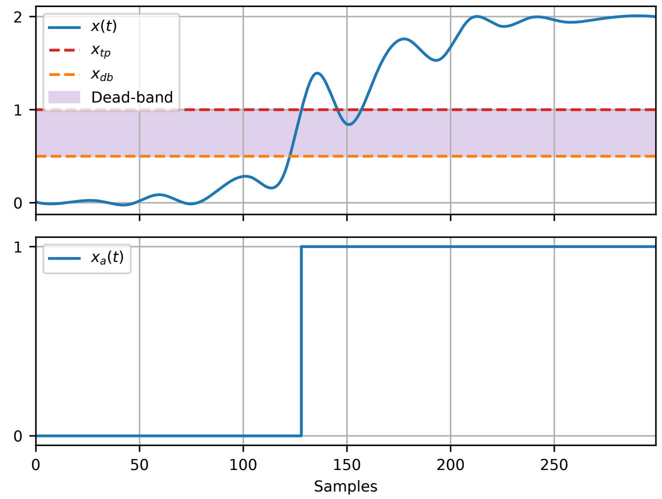

Figure 2. Example of alarm generated with alarm threshold and alarm dead-band.

Table 1. ANSI/ISA - 18.2 Recommendations for alarm dead-band Based on Signal Type

Signal Type	Alarm dead-band
Flow Rate	∼5%
Level	∼5%
Pressure	∼2%
Temperature	∼1%

band values, which were calculated from large operating regions.

The false alarm probability and missed alarm probability are metrics used to estimate the impact of an alarm setting in an alarm system. The false alarm probability (FAP) is similar to a false positive. It measures the probability of an alarm is in alarm state given the normal process probability density function. In the similar way, the missed alarm probability (MAP) measures the probability of an alarm is in inactive state given the abnormal process probability function. The missed alarm probability can be considered as a false negative.

The computation of the FAP and MAP assumes the knowledge of the probability density functions for normal ($p(x)$) and abnormal ($q(x)$) process states. Equation 3 defines the FAP based on the alarm threshold (x_{tp}) and clear threshold (x_{db}). Similarly, in (4), the MAP is defined considering the alarm threshold and clear threshold [Izadi et al., 2009]. It is import to note that in (3) and (4) the alarm is considered of type high.

$$FAP(x_{tp}, x_{db}) = \frac{\int_{x_{tp}}^{\infty} p(x)\,dx}{\int_{x_{tp}}^{\infty} p(x)\,dx + \int_{-\infty}^{x_{db}} p(x)\,dx} \quad (3)$$

$$MAP(x_{tp}, x_{db}) = \frac{\int_{-\infty}^{x_{tp}} q(x)\,dx}{\int_{-\infty}^{x_{tp}} q(x)\,dx + \int_{x_{db}}^{\infty} q(x)\,dx} \quad (4)$$

3. PROPOSED METHOD

Here, an optimization-based approach is used to obtain alarm thresholds minimizing simultaneously FAP and MAP. As it is also possible to associate the reduction of FAP and MAP to the reduction of alarm chattering [Naghoosi et al., 2011], the optimal alarm dead-band parameters are obtained by numerically minimizing (5) [Naghoosi et al., 2011]. Since J is defined using FAP and MAP, then it is also a function of x_{tp} and x_{db}.

$$J = \sqrt{FAP^2 + MAP^2} \quad (5)$$

The role of the alarm dead-band strategy is to prevent nuisance alarm transitions. Considering that an alarm had raised in some instant t_a, the alarm dead-band tries to keep it raised for $t > t_a$. Only when the process has decreased in significant level, below the alarm dead-band, the alarm clears. This concept of alarm dead-band makes possible to define a split strategy on the process data accordingly to an alarm raise. In this way, the normal process region is relative to the data that do not raise alarms based on a given threshold. While the abnormal process region is relative to the history later an alarm raise.

Consider a sample of process data with a occurrence of any abnormality. It is possible to investigate and find an approximation for when the abnormality starts, t_0. Although no alarm is raised in instant t_0, for non-abrupt changes in the process variable. Finally, in time instant t_a an alarm is raised ($t_0 \leq t_a$). An alarm configured only with an alarm threshold will start chattering due to noise. In order force the system to filter the chattering alarms adequately the estimation of FAP and MAP must consider the process data segments which produces chattering alarms and which do not produces chattering alarms.

The process data must be used to estimate the probability density functions for normal and abnormal process data. As discussed earlier, the time instant t_0 represents the moment when an abnormality start to affect the process. Although it should not be used to define $p(x)$ and $q(x)$ since it not adequately presents information on chattering alarms. Therefore, the estimation of the probability density functions $p(x)$ and $q(x)$ must be done using t_a.

To better comprehend our proposed approach consider the following example. A smooth process variable with slow transition was simulated as a first order response to step change at instant t_0 using (6). For this simulation t_0 is defined as 1001th sample (simulation parameter). Figure 3 shows the generated process variable. The red dashed line is a threshold at 3.5.

$$x(t) = \begin{cases} x \sim N(0,1), & t < t_0 \\ 7 - 7e^{\frac{t}{100}} + n \,|\, n \sim N(0,1), & t \geq t_0 \end{cases} \quad (6)$$

In order to estimate the probability density functions the data was split in normal and abnormal sections. Initially, t_0 in (6) is used as split point to demonstrate the importance of the proposed split strategy. In Figure 4 is plotted at the top in blue the normal section of the data and at the bottom, also in blue, the estimation of the probability density function in normal operation. The abnormal section at the top in orange and respectively probability density function at bottom also in orange. Note the heavy tail of the abnormal distribution.

In Figure 5 is plotted the alarm dead-band value obtained by minimizing J. This alarm dead-band value clearly removes all chattering for this variable but creates an alarm dead-band excessively large going until the normal

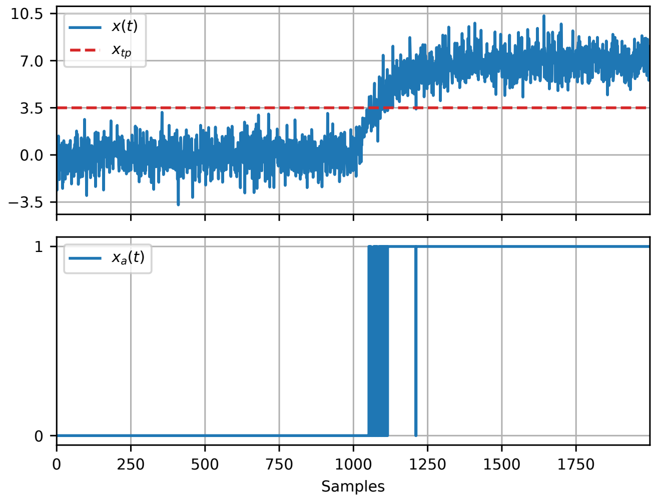

Figure 3. Simulated data: Process with first order transition response.

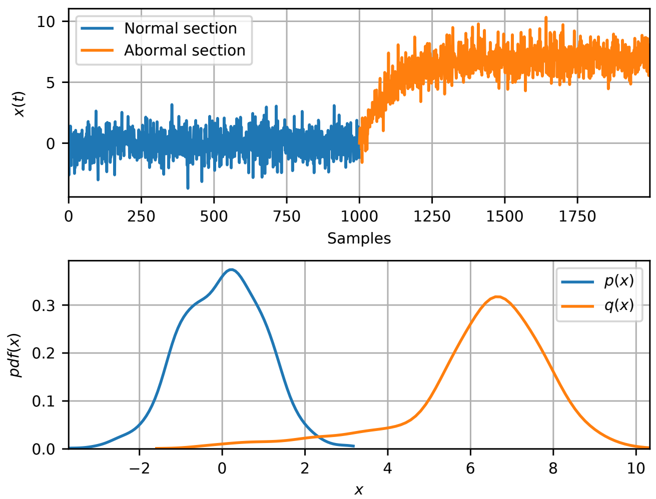

Figure 4. Simulated data: Process with first order transition response and respectively normal, $(p(x))$, and abnormal, $(q(x))$, *pdf*'s.

mean value. In this case, an alarm dead-band from 0 (normal mean) to 3.5 (alarm threshold). A large alarm dead-band may cause alarms to keep raised even when the cause to abnormality had ceased. This behavior must be avoided in alarm systems.

Considering the example process scenario from (6), t_0 is the begin of the abnormality. Previously t_0 is the instant for split the data between normal and abnormal regions. The alarm triggers for this process data in the instant t_a which is greater than t_0. The next examples uses t_a as split point. In Figure 6 the process data in top and the probability density function at bottom, the normal data is in blue and the abnormal data in orange. The new $q(x)$, abnormal probability function, is less skewed and during optimization leads to smaller alarm dead-band.

The new alarm dead-band value for the generated variable is plotted in Figure 7. The alarm dead-band value is less restrictive allowing higher values of the process variable to clear the alarm but keeps the abnormal situation from producing chattering.

This methodology aims to reduce alarm chattering while not producing stale alarms assuming the threshold as a point to define normal and abnormal regions of industrial process operation. Splitting the data based on the instants where the first alarm of chattering regions shortens the tail of the abnormal distribution. This split results in a less biased optimization with smaller alarm dead-band. Which in turn features reduced chattering alarms without causing stale alarms. In the next section is shown a case study a simulated industrial plant.

4. CASE STUDY

A case study using the well-known Tennessee Eastman Process (TEP) is presented in this section [Downs and Vogel, 1993]. The TEP is a simulator for a real chemical process. This process is widely used in process control but

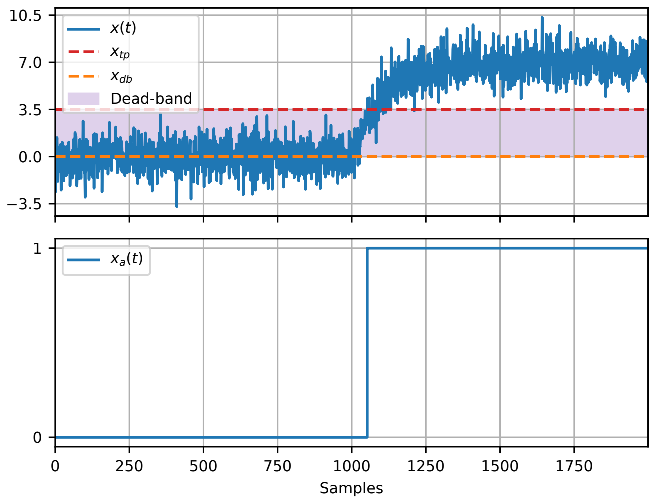

Figure 5. Simulated data: Process with first order transition response with calculated alarm dead-band.

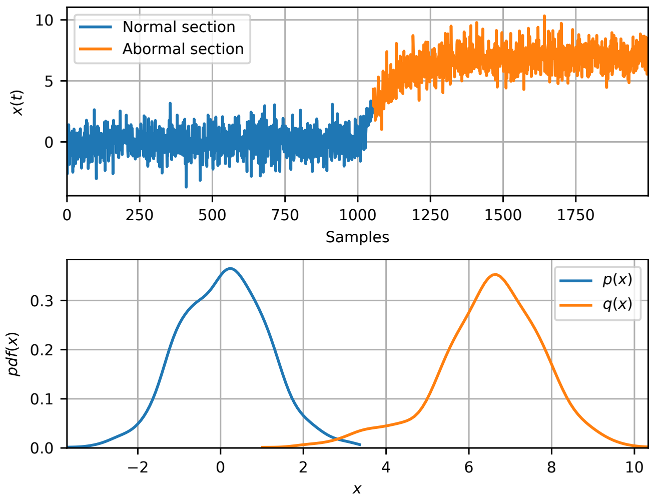

Figure 6. Simulated data: Process with first order transition response and respectively normal, $(p(x))$, and abnormal, $(q(x))$, *pdf*'s with process data split at t_a.

also fits well for alarm management problems. The plant has 22 process measurements and 12 manipulated variables. The process has eight chemical components present with two being the products from four reactants. There are two remaining components: one inert and one byproduct. A set of disturbances is present in the simulator making possible to generate abnormal situations for analysis.

This case study will use a control strategy from Ricker (1995) at the base case of operation. The operation constraints of TEP were used for a classical alarm strategy [Downs and Vogel, 1993]. The data used was generated with sample rate of 1s and the process was under component A feed loss at stream 1 disturbance (IDV6) at the 40th hour after the beginning of simulation. The set of variables used and their operation constraints are listed at Table 2.

Figure 8 presents the constrained process variables and the source of disturbance (X01). Immediately after the 40th hour the measurement of component A feed flow is an abruptly cut and rapidly affects the other measurements. The gray area delimits where the disturbance is active. After approximately seven hours from the start of the disturbance the process actives the interlock strategy and shutdown the plant. Analyzing the effects of the disturbance on the process, only the reactor pressure (X07) and the stripper base level (X15) raises alarms when crossing the dashed lines (thresholds from operating constraints).

The case study was evaluated using several metrics for performance of alarm systems starting with alarm count. To indicate the frequency of alarm occurrence the expected alarm time interval was obtained. Both alarm count and alarm time interval are used to indicate the operator load. To measure the error of the alarm system there will be used the false alarm rate and the missed alarm rate. Similarly to *FAP* and *MAP*, the false alarm rate and missed alarm rate measures when an alarm is active or inactive inappropriately. The main difference is that the false alarm rate and missed alarm rate are calculated based on the alarm data instead of the process data. However, to avoid bias by non-triggering alarms, the abnormal data

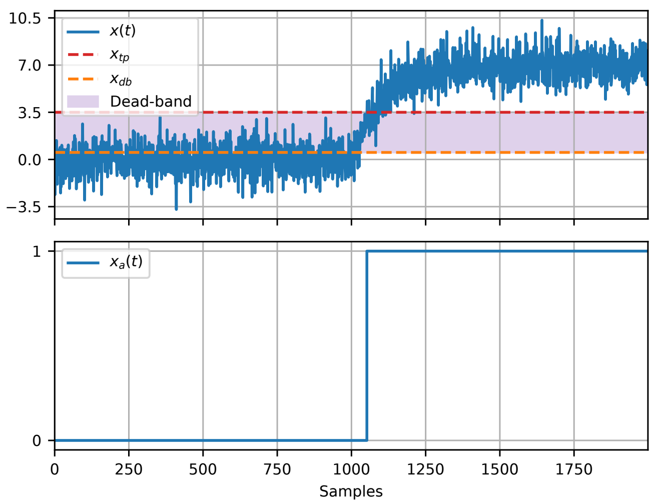

Figure 7. Simulated data: Process with first order transition response with new calculated alarm dead-band.

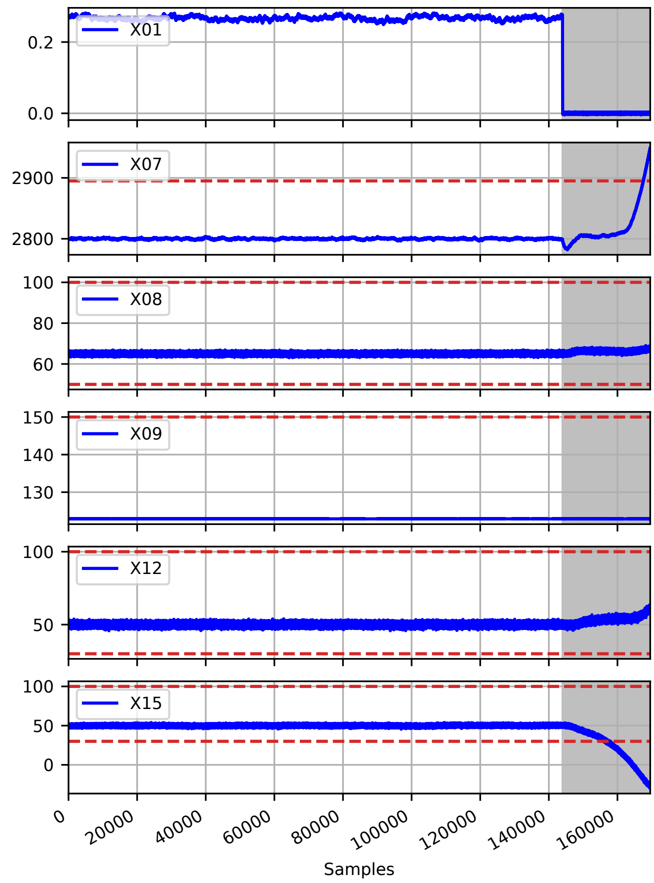

Figure 8. Disturbance Profile: Plot of constrained process variables under disturbance.

is considered later the first alarm raise when calcultating the missed alarm rate. The chattering index was used to indicate how much chattering alarms are present in the alarm signal [Kondaveeti et al., 2013]. Chattering region length is the time between the first alarm raises and the last alarm clear and is represented in a format of "HH:MM:SS".

The alarm dead-band values were defined using standards recommendations from ANSI/ISA (2009) and the proposed method. In Table 3 are the performance metrics for the different alarm configurations.

There is a huge improvement when applying the ANSI/ISA recommendations. The variable X07 have the chattering removed and the variable X15 activated 25 times less alarms, although it presented chattering and 9 alarm occurred.

When applying the proposed method the performance metrics improved even more. The performance metrics strongly related with the threshold (average alarm delay and false alarm rate) do not change, since the threshold is kept fixed. The missed alarm rate reduced to 0 due the fact the alarm did not cleared inappropriately during the disturbance. The chattering index also indicated no chattering also represented in the chattering region length.

The application of the ANSI/ISA recommendation solves the chattering for one variable that has few chattering alarms and has a short chattering interval but fails to

Table 2. Tennessee Eastman Process Operating Constraints

		Normal operating limits		Shut down limits	
Process variable	Tag	Low limit	High limit	Low limit	High limit
Reactor pressure	(X07)	-	2895 kPa	-	3000 kPa
Reactor level	(X08)	50% 11.8 m^3	100% 21.3 m^3	2.0 m^3	24.0 m^3
Reactor temperature	(X09)	-	150° C	-	175° C
Product separator level	(X12)	30% 3.3 m^3	100% 9.0 m^3	1.0 m^3	12.0 m^3
Stripper base level	(X15)	30% 3.5 m^3	100% 6.6 m^3	1.0 m^3	8.0 m^3

Table 3. Performance improvements results

	Operating Constraints		ISA alarm dead-band		Revised method	
	X07	X15	X07	X15	X07	X15
Alarm count	5	226	1	9	1	1
Alarm time interval	3.8 s	9.6 s	-	83.55 s	-	-
False alarm rate	0	0	0	0	0	0
Missed alarm rate	0.0054	0.0401	0	0.0015	0	0
Chattering index	0.5	0.3679	0	0.0284	0	0
Chattering region length	00:00:19	00:36:07	-	00:12:32	-	-
Average alarm delay	06:31:41	03:17:10	06:31:41	03:17:10	06:31:41	03:17:10

completely remove the chattering for both. The proposed method completely removes the chattering for both variables offering the realistically ideal situation of one alarm per variables per disturbance.

5. CONCLUSION

Defining alarm settings for monitoring an industrial process is a challenge for a multidisciplinary team that has to ensure safety during the operation. An already implemented alarm configuration that produces chattering alarms must be revisited in order to remove the chattering alarms. A common practice is the application of alarm dead-band strategies, which greatly reduces the presence of alarm chattering.

At certain conditions optimization of performance proposes an excessively large alarm dead-band values that possibly leads to stale alarms (alarms that remains active for longs periods of time). The method proposed in this paper to determine alarm dead-band values uses an already set alarm threshold for delimit the normal and abnormal regions of operation in order to provide an adequate alarm dead-band value through performance optimization. This approach focus the optimization in reducing the chattering alarms present in the alarm system instead of blindly reduce the estimation of missed alarm probability.

Results obtained from the case study shows great improvements only by applying the recommendation alarm dead-band and even better by applying the proposed method near the ideal one alarm per abnormality. This proposed method can be applied to remove chattering present at transitions from normal operation to abnormal operation.

Future works include an analysis of how the statistic properties of the probability density functions can improve the optimization procedure by weighting the metrics. The penalization of distributions with heavy tails can be done considering measures of symmetry of probability density functions. Also relevant work is to define both alarm threshold and dead-band considering the proposed method. Simultaneously configuring alarm threshold and dead-band can improve overall performance of the system and opens possibilities to use more performance indicators. Finally, the application of the proposed method should be evaluated using a dataset of a real process.

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