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Quantification of alarm chatter based on run length distributions☆

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ABSTRACT

In the process industry, alarms are configured on the control system to provide indication of abnormal events to the control room operators. In the presence of improper design of alarm generating algorithm or lack of appropriate tuning, alarms are announced more frequently than what is typically sufficient to alert the operator, a condition commonly known as 'alarm chatter'. Chattering alarms are the most common form of nuisance alarms. The concept of run length is introduced in the alarm management context to study alarm chatter and an index is proposed to quantify the degree of alarm chatter based on run length distributions obtained exclusively from readily available historical alarm data. Chatter index hence plays a crucial role in routine assessment of industrial alarm systems. Prominent features of the proposed chatter index and its variant are demonstrated using industrial data.

Keywords: Alarm systems; Performance monitoring; Run length distribution; Chatter index; Human machine systems

1. Introduction

The purpose of an alarm system is to alert the control room operator when the process shifts toward unsafe or low quality production. Alarms fall under the second and third out of the eight independent layers of protection (CCPS/AIChE, 1993) according to safety protection layer philosophy. Now-a-days, due to the ease in implementing alarms, the volume of process and system variables that have alarms configured on them has risen exponentially. In a typical plant, most of these alarms are configured during the design and commissioning phase when there is limited knowledge of the nature of the variable being measured and monitored. The two main aspects of alarm design are the selection of alarm generating algorithm and tuning. The alarm generating algorithm or fault detection algorithm can be as simple as a difference between a raw process variable and a fixed alarm limit to as complicated as using machine learning tools for fault classification and are reviewed by Venkatasubramanian et al. (2003). Tuning involves use of simple techniques such as deadbands (also known as hysteresis where a different value from alarm limit is used to clear an alarm), on-delay and off-delay timers and so on. For example, on analog measurements, some control systems have deadband (also known as alarm hysteresis) of 0.5% of instrument range as default tuning parameter for the alarms configured on it. Depending on characteristics like the measurement noise in the signal and type of variable being monitored, a higher value of deadband or another type of tuning such as delay timers (Kondaveeti et al., 2011) may be required for efficient alarm annunciation.

In the presence of inefficient tuning, the rate at which alarms are presented to the control room operator during abnormal events tends to be much higher than what he/she can comprehend and respond to. Most of the alarms during

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Table 1 – A comparison of alarm statistics across various industries with EEMUA benchmark as published by Rothenberg (2009) and is a results of an industrial survey conducted by Matrikon Inc.

	EEMUA	Oil and gas	Petrochemical	Power
Average alarms per hour	$\leq$6	36	54	48
Average standing alarms	9	50	100	65
Peak alarms per hour	60	1320	1080	2100
Distribution % (low/med/high)	80/15/5	25/40/35	25/40/35	25/40/35

these alarm floods are a nuisance to the operator as they limit the operator's ability to identify the root cause variables or critical alarms. Table 1 taken from Rothenberg (2009) compares the alarm statistics over various industries with EEMUA benchmark statistics. It is clearly evident that the alarm activation rates are much higher than the standard recommendation during normal operation.

In the recent past, there has been a significant interest in the field of alarm management in the process industries. There are several incidents following which the investigation reports have pointed at ineffective alarm systems as one of the major drawbacks. In the work by Bransby and Jenkinson (1998), a number of incidents that are attributed to poor performance of alarm systems are highlighted. Several standards (ISA, 2009 and EEMUA, 2007 to name a few) have been published with pointers to effectively managing an alarm system. Rothenberg (2009) has provided a summary of the problems and best practices for managing an efficient alarm system.

There are several stages involved in the *alarm management life cycle* as described in ISA (2009). To make improvements to an already existing alarm system, the *monitoring and assessment stage* is a good entry point into the life cycle. The problems identified in this stage can be rectified in several other stages in the life cycle such as the rationalization and design stage. Identification of nuisance alarms is one of the main objectives in this stage. Chattering alarms are the most common form of nuisance alarms as they fail to provide sufficient time for the operator to respond to each and every occurrence of that alarm. Essentially, chattering alarms conflict with the basic philosophy of each alarm being actionable. Eliminating chattering alarms would improve the quality of alarm data. Good quality alarm data is a prerequisite for advanced alarm correlation analysis like the ones performed by Kondaveeti et al. (2012), Yang et al. (2012) and Ahmed (2011) or the dynamic risk analysis performed by Pariyani et al. (2012) to improve process safety and product quality.

In the academic or engineering practice literature, there are neither standard procedures for identifying chattering alarms nor are there any measures to quantify alarm chatter. The process of rationalizing each alarm tag configured on the alarm system and implementing appropriate design is very time consuming. A feasible approach would be to identify chattering alarms using routinely collected alarm data. Once the chattering alarms are identified along with the amount and nature of chattering, one of the standard design changes can be implemented to reduce the amount of chatter (Izadi et al., 2009). Moreover, such an index for alarm chatter would help in optimal design of a suitable filter using only the alarm data. Reducing alarm chatter using adaptive dead bands based on time series modeling of the process data has been proposed by Hugo (2009). However, this approach requires identification of chattering alarms as a first step and then collection of high frequency process data for modeling and design of adaptive deadbands.

This paper is organized as follows. Section 2 introduces the problem and causes of alarm chattering. Section 3 introduces the concept of runs and run lengths and briefly discusses their application in the alarm management context. In Section 4, a means to quantify alarm chatter based on run length distributions is defined and illustrated with appropriate industrial case studies in Section 5. Section 6 discusses the improvements achieved in the chatter index due to design changes made on two industrial alarm case studies.

2. What is a chattering alarm?

A *chattering alarm* is an alarm that is activated and cleared excessively within a short span of time (similar definitions are presented in EEMUA (2007), ISA (2009) and Rothenberg (2009)). As a rule of thumb, an alarm that repeats three or more times in 1 min is often used as a first pass identification of the worst chattering alarms (ISA, 2009). It is evident that chattering is very vaguely defined and there are no standard guidelines to calculate the degree of chatter on an alarm. As a key performance indicator, there is no acceptable quantity of chattering alarms. Therefore, all the chattering alarms should be eliminated as part of a good alarm management process.

In Rothenberg (2009), chattering alarms are defined to be generated only by digital signals whereas *repeating alarms* which are very similar to chattering alarms are normally caused by analog signals. In this work, no such distinction is made and both of them are referred to as chattering alarms. There are several causes for an alarm to chatter. For alarms configured on analog signals with inefficient design, chattering occurs when the process is operating close to alarm limits. Due to the presence of process and measurement noise, the analog signal tends to cross the alarm limit frequently. Improper alarm design such as inappropriate use of delay timers and latches is often the main cause for alarm chatter on most digital signals.

3. Runs and run lengths

In probability and statistics, a run of a certain type of element is defined as an uninterrupted sequence of one or more identical elements that are preceded and followed by other types of elements or no elements at all. Run length can be defined as the number of elements in a run (Kotz and Johnson, 1988).

3.1. *Brief history of the use of runs and run lengths*

Runs and run-lengths are useful in many fields, including statistical process control, reliability, bio-informatics and finance, for compression and analysis of several forms of data. The interpretation of run lengths is based on the application context. For example, in the statistical process control terminology, *Average Run Length* (ARL) is defined as the average time for which a process remains within some specified control limits. ARL is very useful in evaluating the performance of various process control charts (Shewhart, CUSUM, EWMA and their variants) (Montgomery, 2001). In the Wald–Wolfowitz test (also known as the *runs test*) for randomness, negative and positive runs are defined based on whether the elements are above or below a limit (Wald and Wolfowitz, 1940). Run lengths are similarly defined for the error signal (difference between Set Point (SP) and Controlled Variable (CV)) for evaluating the performance of process controllers (Li et al., 2004). In computer science and information theory, run length encoding is extensively used as a form of data compression.

Statistics based on run lengths provide a reasonable criterion and constitute an evidence for the underlying process. Analysis of the run lengths depend on the nature of the application. For example, the *runs test* for randomness is a different kind of analysis compared to ARL in statistical quality control. The analysis methodology depends on how runs are defined for a particular application (Balakrishnan and Koutras, 2002).

3.2. *Run lengths in the alarm management context*

As mentioned in Kondaveeti et al. (2012), the most important parts of an alarm message are the time stamp (up to seconds precision), tag name (usually has information about the instrument number, plant name and variable type) and alarm identifier (PVLO, PVHI, TRIP, etc.). All these three fields are required to uniquely identify an alarm. It is to be noted that each unique alarm (tagname.identifier) or simply called an alarm, requires a unique operator action. In Kondaveeti et al. (2012), it has been shown that industrial alarm data can be mathematically represented using binary sequences. In this binary time series representation, a value of **1** indicates that an alarm is activated and a message is sent to the operator at that time instant whereas **0** indicates no alarm message is sent. This way of binary sequence representation would capture only the instants when an alarm is sent to the operator and not when it is standing over a period of time. Hence the analysis performed on this type of data is more operators centric and need not include behavior of the process itself.

3.2.1. *Definition*

A *run* in the alarm monitoring context is defined intuitively as the sequence of a 1 followed by uninterrupted 0's before another 1 is encountered in the binary sequence representation of an alarm. The length of a sequence is called the *run length*. Thus a run length can be perceived as the time difference in seconds between two consecutive alarms on the same tag. These two alarms may be due to a single abnormal event or two different abnormal events. During this period, no assumption is made as to whether the operator takes an action to mitigate that abnormal event or not. If an alarm appears, clears and reappears within an interval of 1 s, the run length is assumed to be 1 s. This limitation is due to the 1 s sampling for alarm data which is assumed to be quite reasonable for industrial alarm systems. However, this assumption is violated by controllers that generate events (messages) with higher execution frequency. If the alarm activates, clears and reactivates within the period of least count of the run-length, the run-length for that alarm can be approximated to be equal to the corresponding least count.

3.2.2. *Illustrative example on alarm run lengths*

The second column in Table 2 shows the time instants at which a fictitious level alarm as represented by LI300B.PVHI is announced. The third column in the same table shows the time count in seconds from the start of the first alarm. A time trend for this alarm is shown in Fig. 1. The fourth column shows the run lengths for this alarm. It can be seen that the minimum run length is 2 s for this example and it occurs for the 7th alarm. It means that the process had returned to normal and re-exceeded the alarm limits within those 2 s. This duration is too short for an operator to take appropriate action.

A *run length distribution* (RLD) can be built by summing up and grouping the number of times various run-lengths appear. It is basically a histogram of the run lengths. Fig. 2 shows the RLD for the alarm represented by LI300B.PVHI. The vertical axis represents the frequency or the alarm count (n_r) and the horizontal axis is the run length (r). RLD based on a large amount of alarm data will reveal reliable statistics about the behavior of the alarm. For example, for an alarm that resets once every 10 s during an abnormal event, the RLD will display a peak at a run length, $r = 10$ s.

Table 2 – Run length for a fictitious alarm as represented by LI300B.PVHI based on historical data.

S. No.	Alarm time stamp	Time count	Time difference (run length, r)
1	4/24/2010 12:00:01	1	3
2	4/24/2010 12:00:04	4	3
3	4/24/2010 12:00:07	7	5
4	4/24/2010 12:00:12	12	7
5	4/24/2010 12:00:19	19	7
6	4/24/2010 12:00:26	26	7
7	4/24/2010 12:00:33	33	2
8	4/24/2010 12:00:35	35	5
9	4/24/2010 12:00:40	40	7
10	4/24/2010 12:00:47	47	15
11	4/24/2010 12:01:02	62	–

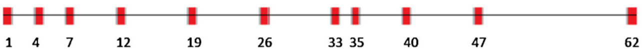


Fig. 1 – Time trend showing alarm annunciations and the respective time count for the alarm represented by LI300B.PVHI.

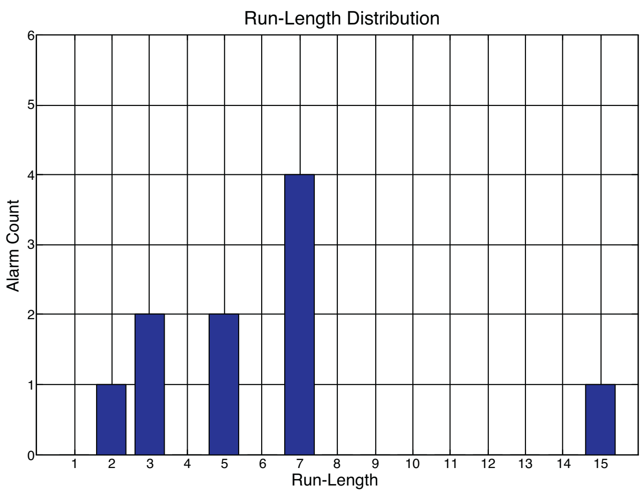


Fig. 2 – Run length distribution for the fictitious alarm represented as by LI300B.PVHI.

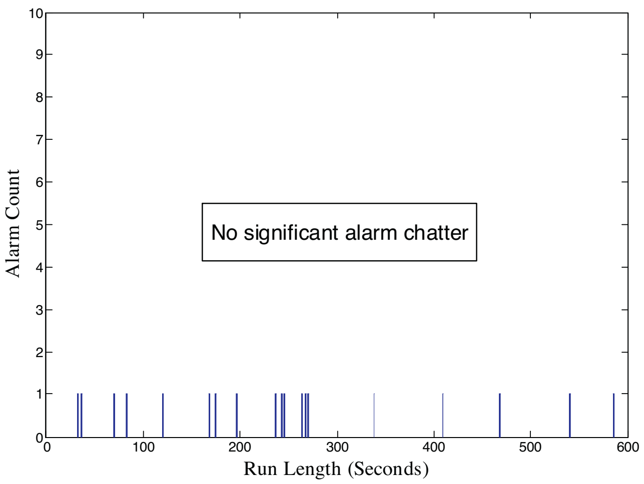


Fig. 3 – Run length distribution for a non-chattering tag.

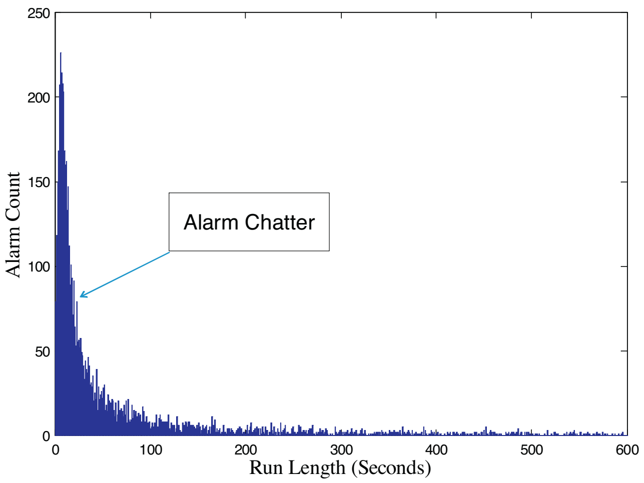


Fig. 4 – Run length distribution for a chattering tag.

4. Chatter index based on the run length distribution

4.1. *Differences between chattering and non-chattering alarms*

Figs. 3 and 4 show the RLDs of two alarms based on real industrial alarm data over a period of one week. From Fig. 3, it is clear that there are not many alarms with short run lengths. The minimum run length observed is 33 s and the distribution is fairly uniform with just one alarm count for each existing run length.

Fig. 4 shows a highly skewed RLD for another alarm. Significant alarm counts exist for run lengths as short as 1 s. This is clearly a heavily chattering alarm. The idea here is to measure the extent of alarm chatter based on these differences in the RLDs.

4.2. *An index to measure alarm chatter*

To calculate a chatter index based on the RLD, it is important to have sufficient data that can represent the behavior of the alarm tag. There are no standard guidelines on the amount of data needed for this analysis. The confidence in the calculation increases with the volume of data available. Once RLD for an alarm is obtained, it can then be normalized to obtain the Discrete Probability Function (DPF). It can be shown that a DPF can be obtained from the RLD by normalizing it with a factor $\sum_{r\in\mathbb{N}} n_r$ which is one less than the total number of alarms on the tag during the considered time period. This is because the last alarm does not have a run length.

$$P_r = \frac{n_r}{\sum_{r\in\mathbb{N}} n_r}, \quad \forall \quad r \in \mathbb{N}$$

where P_r represents the probability and n_r represents the alarm count for any run length r.

The chatter index is then defined by choosing an appropriate weighting function that emphasizes alarm counts with short run lengths. For this purpose, the DPF is weighted with a function whose value decreases with increasing run length. Once the weighting function is chosen, a chatter index can be calculated as

$$\text{chatter index} = \sum_{r\in\mathbb{N}} P_r w_r$$

4.3. *Chatter index based on inverse weighting of the DPF*

Run length is the time in seconds between two consecutive alarms on the same tag. The inverse of the run length would be the instantaneous frequency of occurrence of the alarm. If the inverse of the run length is used as the weighting function, the proposed chatter index (Ψ) can be written as:

$$\Psi = \sum_{r\in\mathbb{N}} P_r \frac{1}{r}$$

Appendix B shows how Ψ is calculated using an example of a fictitious alarm. In spite of the fact that Ψ does not uniquely determine the corresponding DPF, Ψ is useful as a good measure to capture the skewness in a RLD toward shorter alarm run lengths.

4.4. *Properties of the proposed chatter index, Ψ*

Listed below are the properties of the proposed chatter index.

4.4.1. *Theoretical bounds on Ψ*

As shown in Appendix A, Ψ can take values between and including 0 and 1. The higher the chatter index, the higher the amount of alarm chatter. It is easy to deduce that an alarm tag can have $\Psi = 1$ only when there are alarms appearing every second without interruption (i.e. $P_r = 1$ for $r = 1$). And Ψ can take a value 0 when there are less than 2 alarms on the tag during the same period.

4.4.2. *Physical interpretation of Ψ*

The chattering metric, Ψ of an alarm can be perceived as the mean frequency of annunciation of that alarm assuming that the abnormal event prevails for an indefinite period of time. Units of Ψ are alarms/s.

4.4.3. *Ψ is independent*

No tuning parameter is required to calculate Ψ. Once we have the alarm data corresponding to an alarm over a certain time period, calculation of Ψ is straightforward.

4.4.4. *A rule of thumb for the cut off on Ψ*

Although there are no standard procedures to identify chattering alarms, in ISA (2009), it has been mentioned that a frequency of 3 or more alarms per minute can be used as a rule of thumb to identify the worst chattering alarms. Thus a reasonable cutoff on Ψ to identify worst chattering alarms is $\Psi_{cutoff} = \frac{3}{60} = \mathbf{0.05}$ alarms/s.

4.5. *Scope for a modified chatter index*

In defining Ψ, it is assumed that the abnormal event prevails for an indefinite period of time. However, in the following section, it will be shown that the assumption is reasonable due to the fact that large run lengths contribute insignificantly toward the calculation of Ψ.

If we were to know that for a specific abnormal event, nuisance alarms (in the form of chatter) following an actual alarm will not last for more than a specified duration (say τ seconds), all the run lengths greater than τ can be ignored. DPF can then be modified according to a truncated RLD (truncated to τ seconds). The normalizing factor will then be $\sum_{r=1}^{\tau} n_r$. The DPF can be defined as

$$P_{r,\tau} = \frac{n_r}{\sum_{r=1}^{r=\tau} n_r}, \quad \forall\, r \in \{1, 2, 3 \ldots \tau\}$$

$$P_{r,\tau} = 0, \quad \forall\, r \in \{\tau+1, \tau+2, \tau+3 \ldots \infty\}$$

The modified chatter index, Ψ_τ can be written as

$$\Psi_\tau = \sum_{r \in \mathbb{N}} P_{r,\tau} \frac{1}{r}$$

For the fictitious example considered in Appendix B, if we were to know that the alarms corresponding to a single abnormal event will not be separated by more than 10 s, $\Psi_{10} = \frac{(60-1)*3*7}{(60-1)*3*7} * \frac{1}{10} = 0.1$, which is strictly equal to the frequency of occurrence (1 alarm in 10 s). Further, for real industrial alarm data, the best chatter index can be obtained by calculating Ψ_τ over a reasonable range of values of τ and picking the best one (similar to picking the top best factors from a scree plot in Principal Components Analysis). It can be shown that Ψ_τ has the same bounds as Ψ. Additionally, these chatter indices, Ψ and Ψ_τ, can be multiplied by a factor of 60 to represent the frequency of alarm occurrence per minute instead of a second.

5. Industrial case study

In this section, alarm data from an oil sands extraction plant is analyzed for chattering alarms. For convenience, only four alarm tags of interest are shown in this work.

5.1. *High Density Alarm Plot*

The High Density Alarm Plot (HDAP) is useful for visualizing large amounts of alarm data of a plant over a selected time range (Kondaveeti et al., 2012). For every alarm tag that represents a row in the HDAP, the alarm count in each 10 min interval is calculated and color coded. Using HDAP, it is possible to visually identify chattering alarms, related alarms and periods of plant instability. HDAP for just four tags of interest of a plant over a period of one week is presented in Fig. 5. The tag names and identifiers are masked due to confidentiality.

The alarm as represented by tag.id1 shows significant chatter at around 450th bin. There are over 120 alarms over a 10 min interval during that period. During the same time period, there are about 60 alarms in a 10 min interval on the alarm as represented by tag.id3. The alarm as represented by tag.id2 has relatively less chattering but the number of alarms raised during the considered time period is quite high. The number of alarms on tag.id1, tag.id2, tag.id3 and tag.id4 during the one week period are 332, 190, 91 and 59 respectively.

Fig. 6 shows the truncated RLD for the alarm as represented by tag.id1. The RLD is skewed toward shorter run lengths and a large number of alarms (about 80) have run lengths as short as

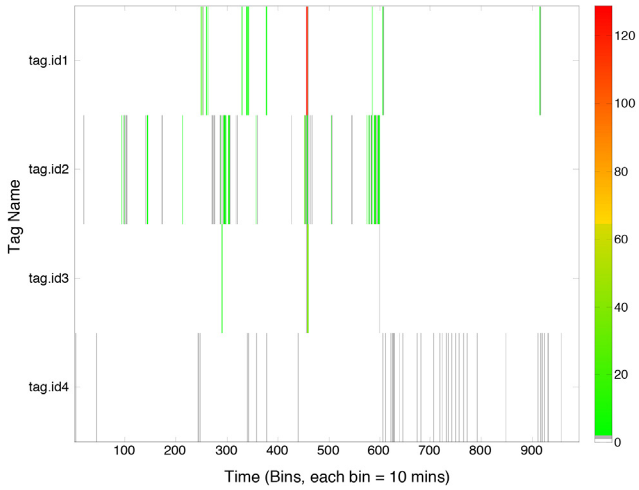


Fig. 5 – High Density Alarm Plot for 4 alarm tags.

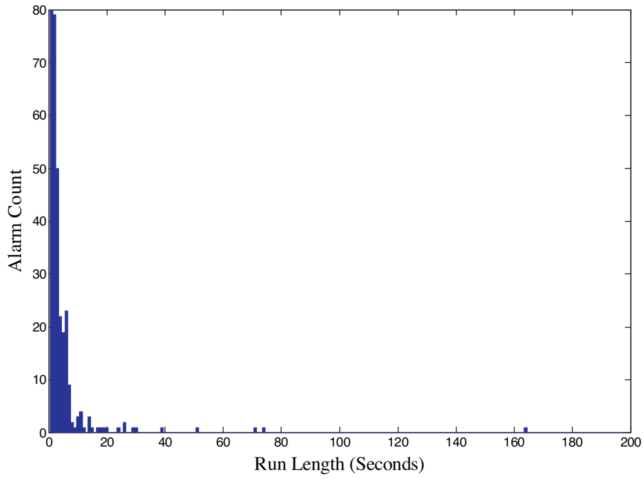


Fig. 6 – Run length distribution for the alarm as represented by tag.id1.

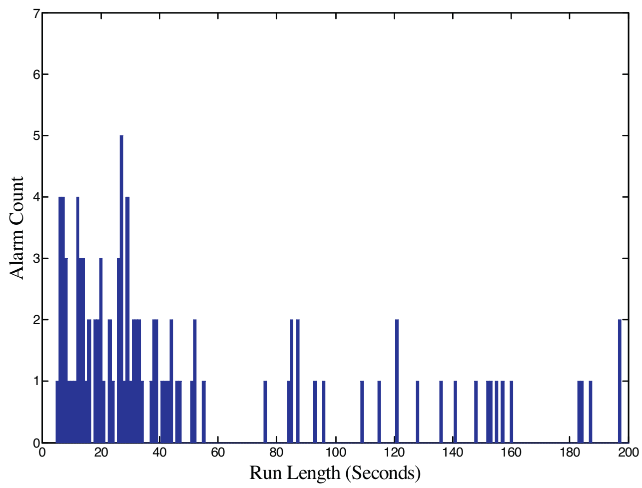


Fig. 7 – Run length distribution for the alarm as represented by tag.id2.

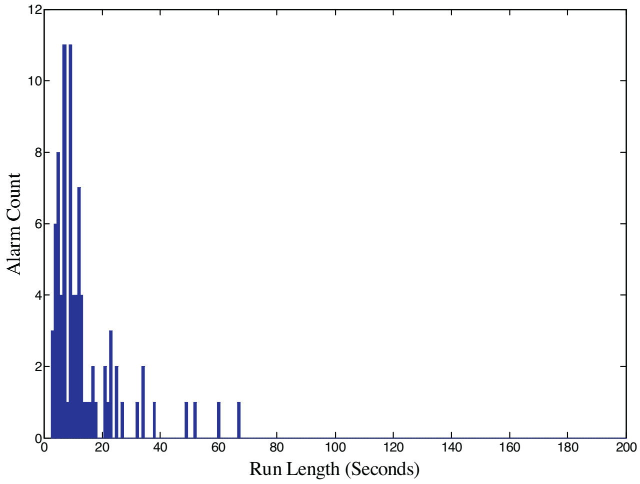


Fig. 8 – Run length distribution for the alarm as represented by tag.id3.

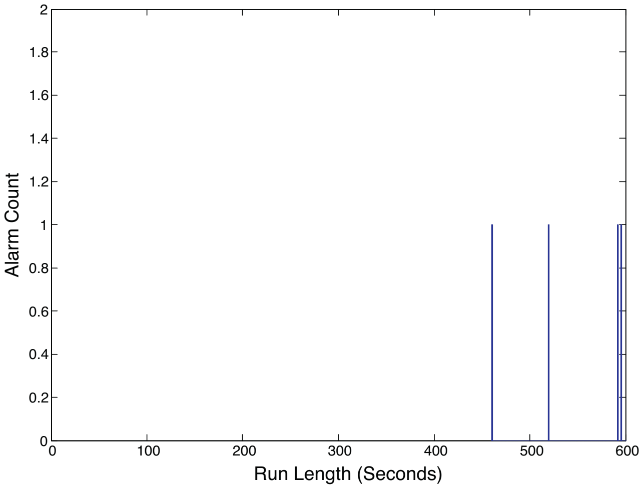


Fig. 9 – Run length distribution for the alarm as represented by tag.id4.

1 s. Therefore the alarm as represented by tag.id1 is expected to have a higher chatter index compared to the rest.

For the alarm as represented by tag.id2, we can see from Fig. 7 that there is just one alarm with the shortest run length of 5 s. However, there are a good number of alarms with run lengths shorter than 100 s.

Fig. 8 shows the RLD for tag.id3. It is evident that most of the alarms have very short run lengths ranging from 3 s to about 70 s. Thus the alarm as represented by, tag.id3 is expected to have a higher chatter index compared to the alarm as represented by tag.id2.

RLD for tag.id4 in Fig. 9 shows that there are hardly any alarms with short run lengths. There is just one alarm with the shortest run length of 461 s. The alarm as represented by tag.id4, is expected to have a negligible chatter index.

5.2. *Chatter indices Ψ and Ψ_τ*

Fig. 10 shows the bar chart of the chatter indices, Ψ and $\Psi_{\tau=600}$ for all the four alarms under consideration. Two striking observations based on this figure are given below.

5.2.1. *Both Ψ and Ψ_{600} show a similar trend*

A small value for $\tau = 600$ is chosen to calculate the chatter index. In calculating Ψ_{600} all the alarms with run lengths

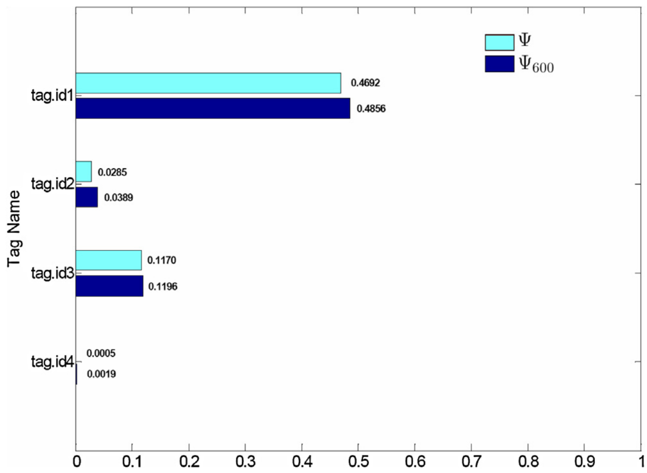


Fig. 10 – Comparison of chatter indices Ψ and Ψ_τ for the four tags.

longer than 10 min (600 s) are ignored. It means that two consecutive alarms on the same tag that are separated by more than 10 min are assumed to represent two different abnormal events. It is interesting to note that longer run lengths contribute insignificantly to the chatter index on an absolute scale. $\Psi_{\tau=600}$ has a slightly larger value compared to Ψ mainly due to the fact that $P_{r,600} \geq P_r \; \forall \, r$. See Appendix C for a detailed derivation.

5.2.2. *Magnitudes of both Ψ and Ψ_{600} agree with visual observations*

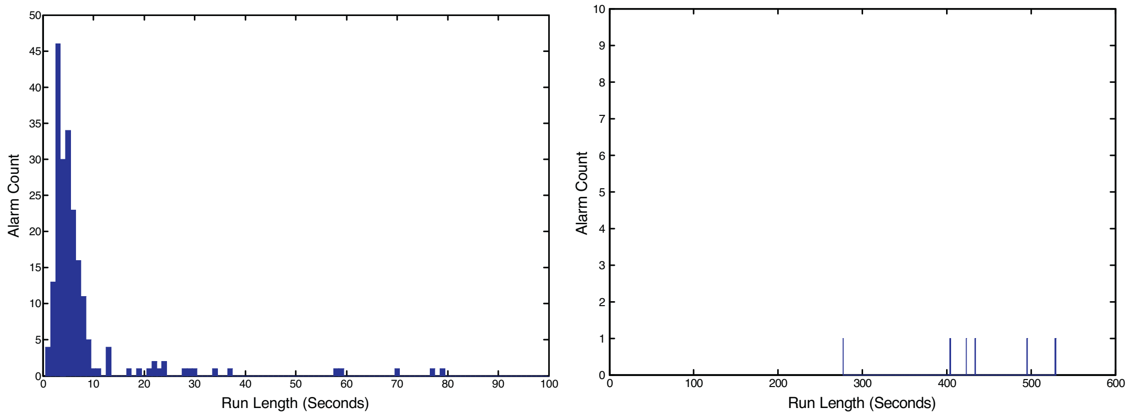
As expected, the alarms as represented by tag.id1 and tag.id3 showed a higher chatter index (in fact greater than $\Psi_{cutoff} = 0.05$) compared to the alarm as represented by tag.id2. The alarm as represented by tag.id4, has an insignificant value for both Ψ and Ψ_{600}. It is to be noted that the alarm as represented by tag.id3 has a higher chatter index compared to the alarm as represented by tag.id2 even though the overall alarm count is higher for the alarm as represented by tag.id2.

6. Improvement in chatter index after redesign of alarms

This section presents a case study where improvement in the alarm run length distribution and hence in the chatter index is observed because of appropriate design changes on each of the two real industrial alarms. The first alarm is a flow tag labeled as tag.id5 and the second one is a density tag labeled as tag.id6. Alarm data was collected for these two alarms for a period of over one month both before and after the alarm design changes were implemented.

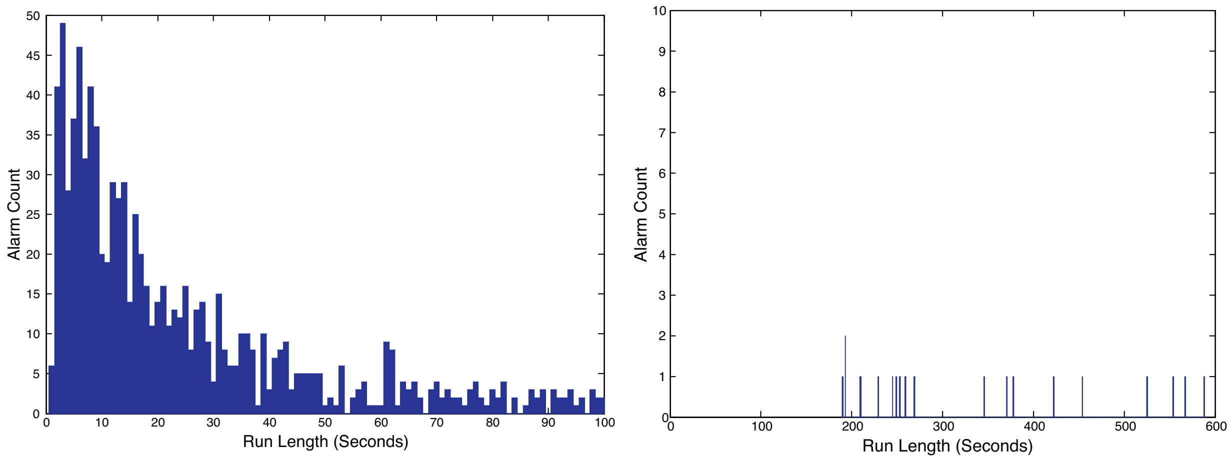
6.1. *Flow tag – tag.id5*

The original alarm design had a deadband of 5%. After reviewing the process data, it was found that there was a significant noise in the underlying process signal and appropriate filtering would help reduce chattering. The following changes were implemented: Moving average filter of length 5 was implemented to filter out the noise; with this change in addition to the existing deadband was kept at 5%.



(a) Before (b) After

Fig. 11 – Run length distribution for the alarm as represented by tag.id5 before and after the design changes are implemented.



(a)Before (b)After

Fig. 12 – Run length distribution for the alarm as represented by tag.id6.

Table 3 – Chatter index before and after alarm design changes are implemented.

S. No.	Tag name	Before		After		Percentage reduction in Ψ
		Alarm count	Ψ	Alarm count	Ψ	
1	tag.id5	218	0.1322	26	0.0009	99.3
2	tag.id6	1248	0.0848	44	0.0021	97.6

6.2. *Density tag – tag.id6*

The original design had a deadband of 1%. After reviewing the data, it was concluded that a larger deadband would help reduce chattering. The following changes were implemented: existing deadband of 1% was increased to 5%.

6.3. *Results and discussion*

Fig. 11(a) and (b) shows the alarm run length distributions of the alarm as represented by tag.id5, both before and after the alarm design changes are implemented. It is evident that there are not as many alarms with short run lengths after the changes are implemented. The shortest run length observed in Fig. 11(b) is close to 300 s. A similar result was achieved for the alarm as represented by tag.id6. The shortest run length observed in Fig. 12(b) is close to 200 s. Table 3 shows the values of Ψ for both the tags before and after the alarm design changes were implemented. It can be seen that there is significant reduction (over 90% reduction in Ψ for each tag) in chattering due to alarm design changes. The design changes implemented in this case study are based on experience and does not take into consideration the effects of detection delay (Adnan et al., 2011) induced due to the changes.

7. Conclusions

Alarm system performance assessment is a crucial step in the alarm management life cycle. In this step, identification of nuisance alarms due to bad design and improper configuration is an important activity. Chattering alarms are the most common form of nuisance alarms and there are no standard procedures to identify them. In this work, a tutorial introduction to alarm chatter is provided and the concept of run length is introduced in the alarm management context to facilitate the quantification of alarm chatter. Chatter index, Ψ is proposed based on RLDs using only the alarm data which is readily available in industrial setting. A variant of Ψ, Ψ_τ, with flexible assumptions is also proposed. It has been shown that for reasonable range of τ, there is no significant difference in the values of Ψ and Ψ_τ.

Ψ can be calculated automatically given the alarm data for an alarm over a period of time and hence reduces the effort required for identifying top chattering alarms as part of routine assessment of industrial alarm systems. A limit on Ψ has been calculated to identify the worst chattering alarms based on a rule of thumb ($\Psi_{cutoff} = 0.05$). The chatter indices proposed, Ψ or Ψ_τ, can be used in optimal design of a suitable filter in order to reduce chattering.

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Appendix A. Theoretical bounds on Ψ

$$r \geq 1 \quad \forall \quad r \in \mathbb{N}$$

$$\Rightarrow 0 < \frac{1}{r} \leq 1 \quad \forall \quad r \in \mathbb{N}$$

Multiplying with $P_r \geq 0$,

$$\Rightarrow 0 \leq \frac{P_r}{r} \leq P_r \quad \forall \quad r \in \mathbb{N}$$

$$\Rightarrow \sum_{r\in\mathbb{N}} 0 \leq \sum_{r\in\mathbb{N}} \frac{P_r}{r} \leq \sum_{r\in\mathbb{N}} P_r$$

But $\sum_{r\in\mathbb{N}} \frac{P_r}{r} = \Psi$ and $\sum_{r\in\mathbb{N}} P_r = 1$ according to definition

$$\Rightarrow 0 \leq \Psi \leq 1$$

Appendix B. Fictitious example of a chattering alarm

Assume an alarm which has a 10 s reset (like a failed pump which is a system alarm). It means that whenever an abnormal event occurs, the alarm rings once every 10 s throughout the duration of the abnormal event. Also assume that the abnormal event lasts for 10 min each time and this event happens once every 8 h (operator shift duration). Assuming alarm data for a duration of one week is available,

$$P_{r=10} = \frac{(60-1)*3*7}{60*3*7-1} \quad \text{and}$$

$$P_{r=(8*60*60-(9*60+50))} = \frac{7*3-1}{60*3*7-1}$$

For all other r, $P_r = 0$. Then,

$$\Psi = \frac{P_{r=10}}{10} + \frac{P_{r=28,210}}{28,210} = 0.0984 \approx 0.1$$

In this fictitious example, the calculated Ψ is very close to the theoretical value of the frequency of alarm occurrence during the abnormal event (1 alarm in 10 s or 0.1 alarms/s).

Appendix C. Proof that $\Psi_{\tau_1} \geq \Psi_{\tau_2} \quad \forall \quad \tau_1 < \tau_2$

Consider an alarm with alarm counts in the RLD represented by n_r. For a finite time τ,

if $\tau_1 < \tau_2$,

then,

$$\sum_{r=1}^{r=\tau_2} n_r \geq \sum_{r=1}^{r=\tau_1} n_r$$

Since $n_r \geq 0 \quad \forall \quad r \in \mathbb{N}$,

$$\frac{n_r}{\sum_{r=1}^{r=\tau_1} n_r} \geq \frac{n_r}{\sum_{r=1}^{r=\tau_2} n_r} \quad \forall \quad r \in \mathbb{N}$$

$$\Rightarrow P_{r,\tau_1} \geq P_{r,\tau_2} \quad \forall \quad r \in \mathbb{N}$$

Dividing both sides with r and summing up over all $r \in \mathbb{N}$,

$$\sum_{r\in\mathbb{N}} P_{r,\tau_1} \frac{1}{r} \geq \sum_{r\in\mathbb{N}} P_{r,\tau_2} \frac{1}{r}$$

$$\Psi_{\tau_1} \geq \Psi_{\tau_2}$$

Hence it has been proved that $\Psi_{\tau_1} \geq \Psi_{\tau_2} \quad \forall \quad \tau_1 < \tau_2$

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