Semantic Analysis of Alarm Response Entries for Plant Health Monitoring

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Abstract
In most health monitoring systems, whenever a 'fault' is detected there is always a requirement for some form of human response or intervention, and in many cases the engineer may decide that it is a false alarm. While everything is done to eliminate false alarms, understanding why the human has decided to ignore an alarm is imperative, and subsequently what that means for improving the performance of the diagnostics sensors. Here the manual reporting log of alarm responses for an in-situ health monitoring system for the general plant equipment in a power station is deconstructed by applying regular expressions to categorise the response. This type of analysis can not only show how often certain types of events occur, but also compare the data at times when a user changed the alarm limits manually to see what was happening in the sensor array.

Keywords: Semantic Analysis, CMS, Intelligent Systems, Industrial applications.

1. INTRODUCTION

Condition Monitoring Systems (CMS) are becoming more routinely used and integrated into everyday situations, from the traditional application of large plant such as power stations and aircraft Health and Usage Monitoring Systems (HUMS)[1,2], to applications that use the On-board Diagnostics (OBD)[3] capability in modern cars. It is therefore becoming more important to not only have CMS that can reliably identify potential fault events with the minimum number of false reports, but also understand the appropriate response and anticipate the user's behaviour.

Current CMS, such as in large plant situations, often use basic algorithms to define alarms, such as a simple threshold, or in the case of a vector signal where phase is important a bounding circle limit. This approach can lead to a substantial number of false alarms, each of which has to be investigated by an engineer and actioned, wasting time and resources: In the case of one system, it was found that 55% of the alarms resulted in no action [4]. While it is possible that more complex algorithms, such as Fourier and higher order domain analysis, can alleviate this issue [5] they also reduce the amount of human influence over the alarms, as the settings for these alarms become too complicated for a ground engineer who is not expert in signal processing. There is, however, additional useful feedback from the user available in the Alarm Log, which can inform the development of both these types of algorithm.

If an alarm in a logged CMS is fired, often the engineer will have to record what the investigation revealed in an alarm log, such as whether it was a known fault or a standing alarm, or if any action was taken, such as:

- adjusting the alarm setting because the system has slowly drifted;
- indicate that there was simply change of state;
- a fault that requires an actual repair.

It is proposed here that the alarm log provided by the engineer can be included in the data that a CMS uses to set and evaluate its alarms, such that an intelligent learning system can understand what type of signal events are false and therefore learn how to identify them as such. It may also be possible for the CMS to learn under what circumstances the limits should be adjusted for drift informed by semantic analysis.

This type of data analysis will require the extraction of semantics within the sentences provided by the engineer in the explanation, a task that is easy for humans but difficult for computers, especially if the sentences are to be actioned. There has been considerable research into the development of Natural Language Processing (NLP) techniques to develop sentence parsers [6, 7], which can separate a sentence into a grammatical construct of meaning. However these systems are far beyond the complexity required for this application and so a much simpler approach is used here, where common alarm log entry components that can be considered semantically important are identified and used to convert the entries into a series of tags that can then be interpreted in a simple way.

2. METHOD

The foundation for this paper has been afforded with access to data from a large size power plant, with rotating shafts and multiple repetitions of redundant subsystem items. The data provided consisted of vibration sensor data recorded and used by the existing condition monitoring and alarm system, alongside a computerised record of alarm events which includes human supervisory comments about the actual operational response. Due to confidentiality agreements and data sensitivity the underlying data used are only available to those who have agreed access with our collaborators. If you wish to know more, please contact the author for details about our partners.

Instead of applying full semantic processing to each alarm entry from a Natural Language Processing (NLP) tool, such as sharpnlp [8], the approach here is an iterative phrase elimination process. Important words and phrases are identified by counting the number of occurrences of a particular ‘phrase’, i.e. a set list of words in a fixed order. If the most common phrases are semantically sensible they can be replaced with meaningful tags, which effectively parses the alarms entries into usable tags. Iteratively applying this analysis will reduce a significant amount of the text into parsed information tags which can be used to inform further analysis. Using full NLP for this deconstruction is not necessary because of the fixed context for the alarm log and there is therefore a relatively constrained number of subjects to include. Using NLP separates a sentence into a meaningful construction of words, and how there relate to each other, and so would require additional post processing to convert the lexical semantic results into meaningful information within the context, i.e. linking the words and relations between them to concepts that an operator would understand.

3. RESULTS

Most common words	
Word	Count
'Alarm'	6797
''	5520
'no'	5176
'to'	3416
'fired'	3206
'concern'	3123
'immediate'	2860
'Accepted'	2529
'on'	2437
'change'	2120
'Of'	2015
'Load'	1797
'Vector'	1718
'step'	1555
'From'	1445
'And'	1442
'Level'	1389
'In'	1332
'Adjusted'	1115
'Reference''	1090
'Signal'	1014

100 Single Occurrence Words
'bound' 'enters' 'momentarily' 'technically' 'sign' 'signs' 'comparable' 'ca' 'series' 'measuring' 'better' 'simil' 'detrimental' '08/05/02' 'spread' 'currentlly' '15/01/02' 'channe' '06/04/02' 'preceded' 'indicate' 'sufferd' 'alaarm' 'odd' 'dropsout' 'states' 'experiences' 'coverage' '18:18' '16/11/01' 'u' 'every' '555' '545' '5min' 'con' 'whereupon' '10/12/01' 'LLR' 'noticeable' 'association' 'lot' 'litle' 'case' 'parammeters' 'seem' '16/10/01' '22/08/01' '24/08/01' 'possib' 'introduction' 'questionable' 'smaller' 'far' 'associa' 'larger' 'involving' 'nogreat' 'suggesting' 'dropped' 'signal/transducer' '26/06/00' 'inadvertently' '06/09/01' 'faullty' 'levelsto' 'Enterered' 'Subsynchroness' 'deployed' 'unsuitable' 'angle' 'slowly' 'mea' 'question' 'existent' '00:51' '06/06/01' '13/02/01' 'moderate' 'speeds' '23:20' '01/03/00' '01/03/01' '52' '146' '17' '133' '29' 'tolerances' 'downs' 'ups' 'trips' '608' 'saved' 'breaks' 'themselves' '21/08/00' '42' '66' '136' 'Commentary'

Table 1: The word statistics results. The twenty most common words to appear in the alarm reports are on the left hand side. Most of the terms are either common connectors, such as prepositions or conjunctions, or terms that are expected in context, such as ‘Alarm’ or ‘Signal’. On the right hand side is a list of 100 single occurrence ‘words’ that are present in the 4939 entries.

Table 1 shows some summary results of the initial word count, which identified 2937 individual ‘words’, in the 4939 Alarm entries. On the left hand side is the twenty most common words. Some of these occurrences are expected within the context being considered, such as ‘alarm’, ‘fired’ and ‘load’, though they also highlight the presence of negation (‘no’) that it is important to be aware of during later stages of the semantic analysis. There are also several grammar words, such a prepositions (‘on’, ’in’) and conjunctives (‘and’, ’of’) that indicate the relationships between the other terms.

At the other end of the scale, 35.3% (890) of the ‘words’ only occur once, though it is these words which may contain more information, as they may describe unique and important events. Table 1 shows a random collection of 100 of these words, and provides a good example of the different types of word that only occur once. There is evidence of three distinct types of ‘word’:

- *Numbers*, which will include dates and times, and are probably important and unique data, and consequentially highly informative;

- *Misspellings*, which included normal words that have run together, or extra letters. These types of mistake will prove difficult to rectify in a generic way;
- *Real Words*: Words that are correctly spelt and have a specific meaning.

These results are informative as they indicate the problems and types of information that are stored in the alarm reports. However, the context of items, particularly the numbers, that is required to form the basis of a useful analytical tool. In order to extract this context, a certain amount of parsing is needed to convert the entries to a format aminable to a computer system. Here the parsing is performed by identifying the most common phrases, noting whether these can be converted to a meaningful tag, and then applying the phrase as a part of the parseing.

Two Word Phrases	Count
immediate concern	2816
no immediate	2815
alarm accepted	2584
alarm fired	1477
fired on	1474
Vector fired	1466
step change	1388
no step	1340
change alarm	1277
reference adjusted	962

Three Word Phrases	Count
no immediate concern	2772
no step change	1304
step change alarm	1166
Vector fired on	1083
change alarm accepted	1033
alarm accepted reference	811
alarm accepted no	789
alarm left standing	772
accepted reference adjusted	761
reference adjusted no	695

Four Word Phrases	Count
no step change alarm	1129
step change alarm accepted	1011
alarm accepted reference adjusted	761
alarm accepted no immediate	679
adjusted no immediate concern	676
reference adjusted no immediate	676
accepted no immediate concern	675
accepted reference adjusted no	591
change alarm accepted reference	582
no immediate concern alarm	529

2 Word Phrases	
Total Number of Phrases	= 103531
Number of Different Phrases	= 13560
Single Occurrence	= 6419 (47.34%)
3 Word Phrases	
Total Number of Phrases	= 98606
Number of Different Phrases	= 23296
Single Occurrence	= 12925 (55.48%)
4 Word Phrases	
Total Number of Phrases	= 93682
Number of Different Phrases	= 28788
Single Occurrence	= 17134 (59.52%)

Table 2: Phrase List Counts - each table shows the top ten most common phrases of 2, 3 and 4 words along with their frequency within the alarm reports. Note how the most common two word phrases are often overlapping components of the three and four word phrases.

From Table 2 there two obvious results: the first is that 'No immediate concern' is the most common 3 word phrase, and a phrase that is semantically isolatable, such that it has a meaning that is not dependent upon other sentence components. Specific content meaning can change, i.e. something specific is of no immediate concern, but the phrase will not change its meaning, e.g. it cannot be (reasonably) negated (i.e. 'Not') because it already is a negative.

The second phrase that could can be considered its own semantic unit is 'Alarm Accepted'. Note how the two most common 2-word phrases are the overlapping components of this phrase. This may seem like an expected result and obvious point, but it becomes important for identifying what phrases can be reduced to a semantic meaning in their own right, such as "No Immediate concern" against common phrases such as "immediate concern", as the latter can be modified (e.g. by adding 'No', even though it is a more common phrase than "no Immediate concern".

There are some phrases that may be able to stand semantically isolated from the other, but only by investigating the longer phrases, i.e. the words around the identified phrases. If

The phrases identified as semantically isolatable are then replaced with a tags in-situ, and the process is repeated, ignoring the tags such that the analysis produces a new set of most common phrases each time, until the most common 3 words phrase appears in fewer than 40 (~1%) of the alarm entries.

At the end of this iterative comparison, over 80% (by word count) of the text is converted to meaningful tags, though this only completely tags about 5% of the alarm entries, and produces a list of 115 tags. Semantically these tags can be separated into a number of classes:

- **Objects**: These are items that can have other terms applied to them, but the modifier doesn't change the meaning of the item. Examples include signals, levels, or items such as the CMS or Unit itself.
- **Events**: These are system wide events that happen outside the CMS, such as refuelling, repairs, or low load conditions. Grammatically they are similar to objects, in that their meaning can be used to anchor the rest of a statement.
- **Actions**: These are actions that are applied to the plant or CMS as a result of an alarm, such are resetting the CMS, or adjusting the alarm parameters.
- **Alarms**: These tags identify parameters or types of alarm, for example if there is a Vector, Step or Circle radius that is important. Also tags that indicate if the Alarm is left standing or disabled, etc.
- **Transition Status**: For any object, indicates the behaviour of the object (signal or plant), e.g. increasing, decreasing, stable, noisy, failed etc.
- **Temporal**: Indicate when in an Event, or Transition, the Alarm or a connected Action occurred. i.e. During, at end of, before, after.
- **Relationships**: simple connectors, indicating direction of causality or conjunction of events (i.e. A and B happened)
- **Zonal**: Tags that identify specific vibration zone events - which zone and if the indication was for near zone or in zone.
- **Notes**: These are tags that have very specific meaning and are not usually expected to be connected with other tags. "No Immediate Concern" tags are included in this case.

The reason for having such a complex set of tags is that, while some sentences can be usefully converted into tags in their own right, such as "No Immediate Concern" or "Alarm Accepted", in a large number of cases the understanding of the sentence must come from a conjunction of tags. An example of this might be "Alarm due to rising load": here the sentence is currently parsed as <alarm><caused><load><rise>, so that this alarm report can be tagged as both an effect of a general Load incident, and a load rising event. The tags allow phrases with the same meaning but with different construction (e.g. 'fired on', 'fired as a result of', 'fired due to', 'fired from', 'fired following', etc.) to reduce to the same tag. This tag can then be interpreted within the context of the adjacent tags, so if two alarms were 'fired on reducing load' and 'fired due to increasing current', the same tag indicates semantics of the sentence i.e. that what comes next was cause of the firing, but many other possibilities are available for the surrounding context.

It is also possible, without any secondary stage of semantic context, to extract meaningful information about the alarm entries at this point.

	Count	Proportion of Entries
Alarm Status		
Alarm Accepted	2604	52.7%
Alarm Disabled	95	1.9%
Alarm Reset	123	2.5%
Standing Alarm*	881	17.8%
Alarm Reference	55	1.1%
Vibration Zone Observations		
In Zone A-B	16	0.3%
Near Zone C-D	119	2.4%
In Zone C-D	125	2.5%
Plant Events		
Refuelling	516	10.4%
Boiler Shut Down	80	1.6%
Outage	537	10.9%
Run Down	4	0.1%
Return to Service	655	13.3%
Connected Sources		
CMS	321	6.5%
Sensor	3	0.1%
Load	1297	26.3%
Actions		
Flagged	280	5.7%
Adjustment Made	104	2.1%
Something Failed	217	4.4%
Fix Required	27	0.5%
No Action Required	3136	63.5%

Table 3: Statistical Overview of tags meanings. These results are not inclusive of all tags, as some of the tags need an extra level of semantic decoding. The numbers are indicative of how often a reference appears in the alarm log, but may be connected to another tag which actual changes what happened, i.e. was the adjustment made to an alarm reference. *a Standing Alarm is a known alarm that is left intact (no adjustment) by the engineers for indication purposes.

The results in Table *3* are not a comprehensive list of tags, as a large number of the tags produced require another level of semantic analysis to have meaning, and those meanings might be individually important to only a single alarm incident report. What these results do indicate is the number of reports that have a particular theme connected with them and so indicates the scale of the false alarms: if it is considered that a false alarm was when no action was required, among other things, then in nearly 60% of the alarms are false, while a definite fix was only required in ½ of 1% of alarms.

These results also identify not only what information is provided by the alarm entries that could be used by the CMS system to compare signal events and their response, such as comparing a false alarm with an adjusted alarm to learn a trend in a signal adjustment, but also what information it would be proactively useful to give the system, e.g. informing the CMS of a plant event, such as a rundown.

4. CONCLUSIONS

The purpose of this study was originally to identify the meaning in alarm log entries such that particular alarms could be could be tagged and identified for intelligent data analysis of past signal events, and so create intelligently adaptive limits.

While the current study only implements the first part of this analysis, it can be used to condense the text into useable and informative tags that can then be used to sort the data signals into types of event that watch for triggers. For example, if all the run down triggered alarms can be identified they will serve as the basis data for a learning system which can then compensate for the signal occurrence during this event. Other more specific but vaguely correlated events could also be analysed, such as interrelation between signals at times when an engineer decided to adjust the alarm parameters for drift.

The analysis in this paper shows that there are a several aspects to keep in mind when analysing the meaning of alarm entries, but extracting this meaning has very definite advantage in its potential to inform intelligent Condition Monitoring Systems. Knowing which alarm events on which signals are important or not, and knowing if action was taken or not are components that can be fed to an artificially intelligent learning machine of some description and help reduce false alarms. It can take into account when there appears to be correlation between signals that are only linked in that period for an explicit reason, or simply understand which alarms are left standing.

However, this study has highlighted several important factors that can inhibit this semantic extraction, without using a fully informed natural language processing algorithms. The first is human error in the text entry, either poor spelling or mistyping which mean that direct phrase comparisons fail at this point. The second is an inconsistency in phrasing between entries, possibly the result of different users. For example, there were 10 phrases that were identified as meaning ‘the alarm was caused by’, such as ‘fired on’, ‘fired as a result of’, ‘fired due to’, etc.

These two issues could be minimized by having an intelligent text prediction input suggestion, which corrects spelling on the fly while encouraging users to use standard phrasing in the data entry stages.

A third issue is that while some phrases can be tagged as informative in a standalone sense, (e.g. knowing an alarm had no action taken, irrespective of the other information in the log entry, is useful to know as it indicates a false alarm) there are some phrases that are informative only in conjunction with other tags, such as ‘rising’, ‘falling’ or numeric values. This lack of context requires another level of semantic analysis that extracts this information, and it should be possible to do it in a more generic way such that when the meaning of the two tags is known there is no need to hold knowledge of that specific combination of tags.

The final issue is the rarity of some phrases and their meaning. In some cases there are events which don't happen often, and the system may have to be informed of the meaning of a new phrase, such as '<sensor><fault> WR 1630499 <flag><fix>' where the specific meaning of the unparsed 'WR 1630499' may have to be noted to the system, although simply tagging it as an object in the first stage of parsing would be enough in this case.

In summary, there is certainly an extra dimension of information to be derived by extracting the tags from the alarm logs which can inform the next stage of data analysis. Automating this process is difficult due to the variation in human entry behaviour, such as spelling and phrasing, but by using assistive predictive text these variation can be minimised so the circumstances surrounding an alarm can be better understood by the system. This should give the system the capacity to learn when and why an alarm has triggered and when it is adapted because of drift. There is still plenty of work to be done on connecting events on a signal and across signals, and then using this information to produce a more intelligent way of reducing false alarms, but this study has indicated the potential of at least one stage of this process to work alongside the problems it faces.

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