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Improving Operational Efficiency Through Alarm Management in Water Treatment Processes Using Artificial Intelligence

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Abstract: Water Treatment Plants are controlled by modern industrial process control systems like SCADA or DCS. This facilitates to monitor, control, and troubleshoot water treatment processes and helps in maintaining continuous supply of water with adequate quality. At times and in contrary, these systems hamper process control by generating far too many alarms than needed. Many of the alarms are nuisance in nature and do not indicate any real abnormality. The true alarms which require prompt operator actions to normalize the process are often buried in the pool of nuisance alarms causing significant challenge for operator to take appropriate corrective actions in a timely manner. Many of the past major incidents occurring in the major process industries were attributed to operators' inability to identify true alarms and take necessary actions. In this paper, we propose an Artificial Intelligence (AI) based pattern mining and advisory system to improve operational efficiency in alarm management. The identified alarm patterns bring out actionable insights in data by (i) identifying nuisance, chattering, redundant alarms, and (ii) Alarm response Pattern. A novel technique for sequential pattern mining in industrial Alarm & Event log data was developed based on State-of-the-art AI based association rule and pattern mining. The efficacy of the proposed method for systematically improving alarm management system in an actual plant environment is currently being studied in a water treatment plant in Singapore.

Keywords: Alarm Advisory and Decision Support, Alarm and Event Analysis, Alarm Response Pattern, No Action Alarms, Redundant Alarms

1. Introduction

One of the major challenges for the Water & Wastewater Industry highlighted in ARC Market Analysis Report [1] issued in Jan 2019 is lack of skilled labour and the suggested solution is automation of process control, analytical and testing needs. Alarm systems are the essential constituent in all modern computerized process automation systems. Alarm systems play a vital role as far as safe and efficient operations of modern industrial plants such as chemical, petrochemical, petroleum refineries, water treatment and power plants [2, 3] are concerned. The primary purpose of the Alarm systems is to quickly flag the occurrences of any abnormal situation, so that operators can take essential corrective actions to bring the process back to its normal operating condition. The main problem in most of the existing industrial alarm systems is that they generate far too many alarms that operators can effectively handle. This phenomenon is referred to as "Alarm Overloading" in Wang et al, [4]. The phenomenon of Alarm Overloading is clearly manifested in Table 1 [3, 6], wherein the statistics of 3 Key Performance Indices (KPIs) of alarms systems, based on a study of 39 industrial plants ranging from oil and gas, petrochemical, power, wastewater treatment plant and other industries are shown. The corresponding benchmark KPI values as per the EEMUA-191 guideline [5] are also reported in Table 1 for comparison. It can be seen from Table 1 that the statistics of KPIs from various industries are far away (around 6 to 9 times more) from the EEMUA benchmarks.

Table 1. *Comparison of Alarm System KPIs across various industries with EEMUA benchmark.*

KPIs	EEMUA [5]	Wastewater Treatment Plant [6]	Petrochem [3]	Oil-Gas [3]	Power [3]
Average Alarms/day	144	1800	1500	1200	2000
Peak alarms/10 min	10	280	180	220	350
Average alarms/10 min	1	7	9	6	8

The effects of alarm overloading are particularly harmful to the crucial role played by alarm systems. The nuisance alarms are mainly responsible for the phenomenon of alarm overloading [4]. The nuisance alarms, as the name suggests, do not actually indicate any abnormal condition, and only cause distractions to plant operators. The true alarms that indicate an abnormal situation and require operators to take remedial measures are often hidden within large number of such nuisance alarms and are often missed by operators. As a result, they may work on the alarms that are less important or attempt to struggle with all alarms or completely give up on the alarm system. Therefore, there is a need for a system to systematically manage the alarms for improving the operational efficiency by providing intelligent advisory and decision support to the plant operators in real time. In this paper, we propose a novel Artificial Intelligence (AI) based approach using Yokogawa developed state of the art sequential pattern mining methods to analyse a large volume of historical Alarm and Event log data in a systematic manner to identify many hidden patterns that are useful and important and turn them into actionable information. The extracted alarm patterns can provide intelligent advisory to the plant operators by identifying the (i) Nuisance alarms (such as - Chattering Alarms, Redundant Alarms, Alarms with no operator actions), (ii) True and consequential Alarms, (iii) Alarm response patterns for true alarms. The proposed methodology for improving operational efficiency and alarm management by identifying alarm and event patterns automatically is explained in Methods section along with some illustrative examples from a water treatment plant in Singapore. Finally, in the Conclusion section a summary and the direction of future work is presented.

2. Methods

The flow chart of the proposed methodology is illustrated in Figure 1. At first, chattering alarms are identified and removed from the historical Alarm & Event log data. According to the industrial standard ANSI/ISA-18.2 the chattering alarm are defined as one that repeatedly transitions between the alarm state and the normal state within a short period of time [7]. Due to this, there is no time for operators to analyze such alarms and take actions. Two closely related nuisance alarms are the fleeting and repeating alarms. Fleeting alarms also have short-time alarm duration, but do not immediately repeat. Repeating alarm on the other hand repeat almost immediately after its recovery, but do not necessarily have short-time alarm duration [7]. Chattering alarms are usually triggered due to random noise and/or disturbances on process variables configured with alarms, or due to faulty instrument, especially when the process variables are operating close to their alarm limits [5].

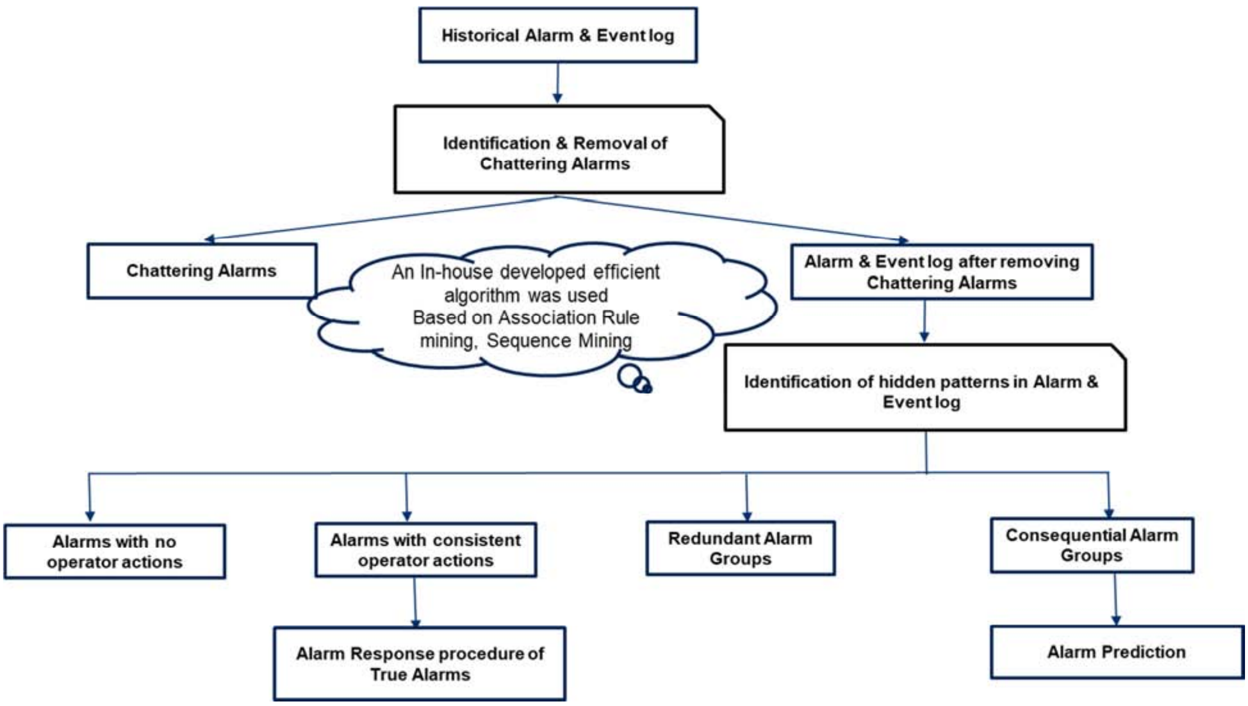

Figure 1. *Flow chart of the proposed methodology.*

An efficient algorithm developed by Yokogawa [8] is used for identification of chattering alarms (including fleeting and repeating alarms) and their subsequent removal from Alarm & Event log data. After identification of the chattering alarms various alarm rationalization activities that can be carried out to get rid of them include alarm configuration changes such as modifications in alarm hysteresis, alarm limits settings, ON-OFF delay timer settings [9, 10]. If the chattering alarm is due to excessive noise in process variable configured with alarm, then appropriate filter can be applied to remove the noise and to smoothen the signal [11]. Again, if the chattering alarm is caused by the oscillation, then the root cause of oscillation (e.g., improper PID controller tuning, stiction in control valve) must be identified first and subsequently the appropriate corrective actions (e.g., re-tuning of PID controller, valve maintenance) should be taken to remove the root cause of the oscillation [12].

We applied this efficient chattering alarm identification and removal algorithm on a historical Alarm & Event log data from a water treatment plant in Singapore. The algorithm was able to identify the chattering, fleeting and repeating alarms present. It was found that the top 16 (in terms of alarm count) identified chattering alarms (including fleeting and repeating alarms) contributes to about 70% of total alarm count. These 16 identified chattering alarms were presented to the plant personnel and the corrective actions were subsequently taken to resolve these chattering alarms. Furthermore, removal of these chattering alarms after implementing the corrective actions resulted in a significant improvement in overall performance of the Alarm Management System. A graphical representation of Alarm System Performance is shown in Figure 2 as per EEMUA [5] guidelines, whereby the ideal state is at average alarm rate of 1 alarm per 10 min and maximum average alarm rate of 10 per 10 min.

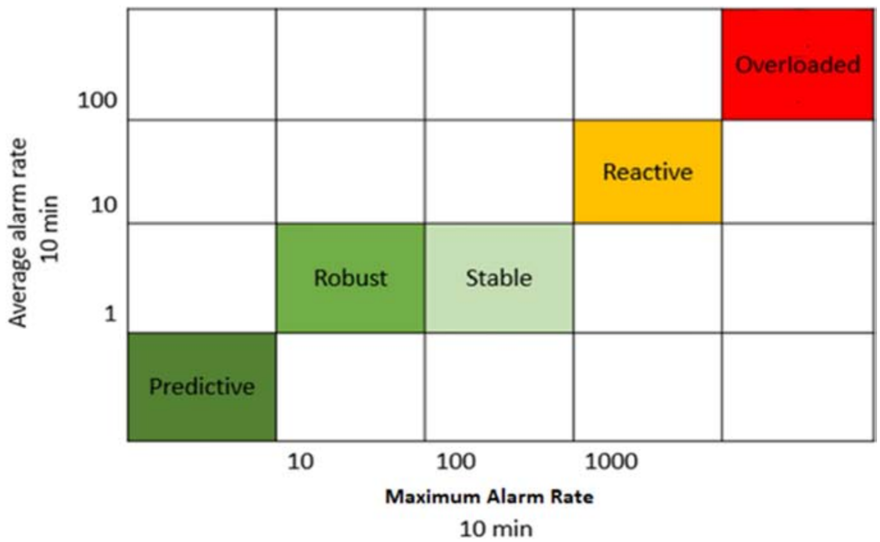

Figure 2. *A graphical representation of Alarm System Performance as per EEMUA [5] guidelines.*

A significant (>80%) reduction in alarm count in most of these chattering alarms can be achieved after implementing the corrective actions. For example, valve exercise was implemented to manage motor feedback error and hysteresis was implemented in SCADA to manage alarm occurrence in transmitter.

After removing the chattering alarms, the de-chattered Alarm and Event log data was used to identify the useful and interesting patterns hidden in the data. It should be noted here that the chattering alarms are considered as noise in Alarm & Event log data and hence they should be removed first to remove spurious patterns before applying any pattern mining algorithm. We have used an AI based sequential pattern mining algorithm developed and patented by Yokogawa [8] for identifying the useful and interesting patterns in the alarm and event log data. The detail of the algorithm is not discussed in this paper due to its confidentiality. Various other nuisance as well as true alarms that can be identified from the extracted alarm & event patterns are discussed next.

2.1. Identifying the Alarms with No Relevant Operator Actions

The proposed approach can identify certain Alarm patterns in which consistently there is no related operator action in between every occurrence and recovery of an alarm. Such alarms are probably not critical since they do not need immediate operator intervention to bring them back to normal and could be a good candidate for alarm suppression or logging or removal (See Figure 3 below). These alarms could be termed as "No Action alarms" since they do not require any operator action. Thus, identification of these alarms and subsequently their suppression in case they are found to be not necessary could lead to significant reduction in alarm load.

Figure 3. *Alarms with no action (Potential candidate for Alarm Suppression).*

We applied the proposed approach to de-chattered Alarm and Event log from a water treatment plant in Singapore. The proposed algorithm was able to systematically identify some alarms that do not have any relevant operator actions. It was found that the top 20 no-action alarms contribute to about 7% of total alarm count. A detailed investigation is further required on these identified no action alarms to determine if they are indeed necessary. The unnecessary alarms can then be considered for suppression.

2.2. Identifying Alarms with Consistent Operator Actions – Alarm Response Pattern

The proposed approach can also identify certain patterns of Alarm and Events in which consistently there is a certain set of related operator actions that are performed regularly in between almost every occurrence and recovery of an alarm. Such alarms are called alarms with consistent operator actions. Probably, these alarms are true alarms since they demand operator actions and must be handled in a certain specific manner in order to bring them back to the normal state. Therefore, identifying such alarms and the sequence of necessary operator actions that follows the alarms can be captured in a knowledge repository to help the operators in easily handling them (See Figure 4 below). The sequence of operator actions required to handle such alarms can be standardized and documented during the Alarm Rationalization Process.

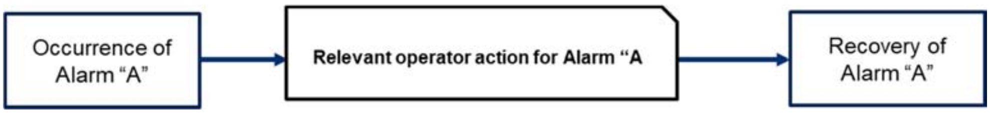

Figure 4. *Alarms with relevant operator actions (Potential candidate for Standardizing Alarm Response Pattern).*

One example of alarm response patterns with consistent operator actions are presented next (See Figures 5 below). These examples are obtained by analyzing historical alarm and event log data from a Water Treatment plant in Singapore. Sequence of operator actions between Sodium Hydroxide Tank Motorized Valve Motor feedback error Alarm activation and recovery are presented below in Figure 5.

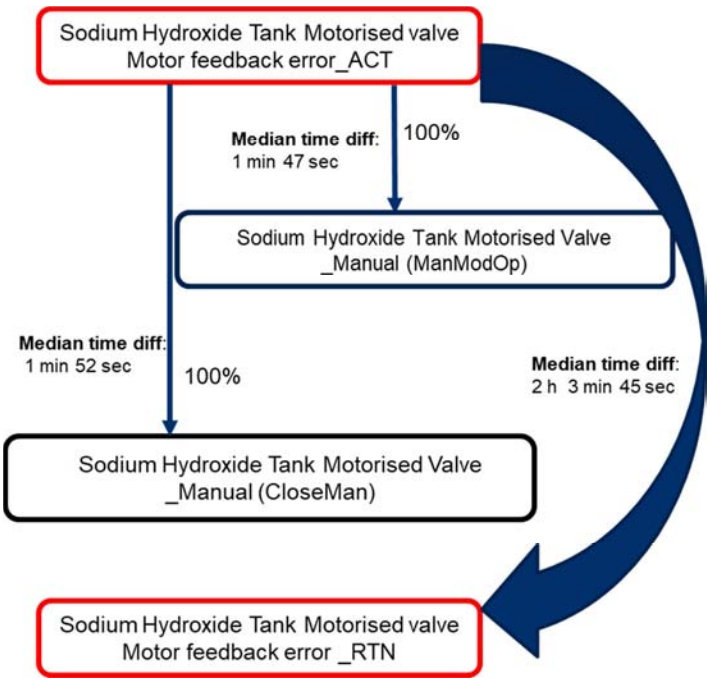

Figure 5. *Sequence of operator actions between Sodium Hydroxide Tank Motorised Valve Motor feedback error Alarm activation and recovery.*

Here, Sodium Hydroxide Tank Motorised Valve Motor feedback error Alarm is handled by taking this motorized valve first in manual mode of operation and then exercising the valve manually.

The identified Alarm response pattern presented above was discussed and verified with the plant operators and engineers. Thus, the extracted alarm response patterns can be further developed to provide valuable advisory to the new or less experience operators on how to handle certain alarms.

2.3. Identification of Alarm Grouping / Clustering

The proposed method can identify a group or cluster of alarms that often occur together in a sequential manner. Such alarm pattern sequences can be further classified into two categories based on the time difference between the alarms in the sequence – *(i) Redundant Alarms:* The group of alarms that occur within a very short interval of time (typically within less than 5 min) from each other and *(ii) Consequential Alarms:* The group of alarms that occur with a significant interval of time (typically 5 min or more) from each other. Figure 6 below presents the steps involved in identifying the redundant and consequential alarms.

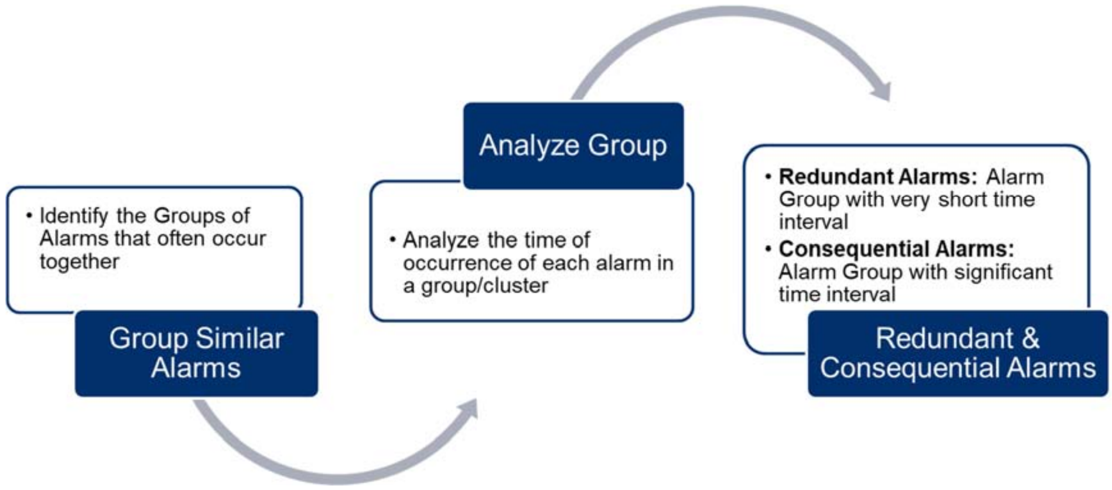

Figure 6. *Steps involved in identifying the redundant and consequential alarms.*

Further, following actionable insights can be inferred from the identified alarm groups/ cluster.

1) Suppression of redundant alarms

Redundant Alarms are most probably activated by the same underlying root cause. Hence, they can be suppressed since they do not provide any additional information. This will reduce Alarm rate significantly.

2) Grouping of redundant alarms

The redundant alarms are most likely to be generated by the same underlying cause and all of them possibly indicate the same problem and hence, require the same corrective actions as well. So, all the alarms in a redundant alarm group are not necessary and may be just one of them would be enough to indicate the actual underlying problem. Thus, all the alarms except one representative alarm can be suppressed or removed, since they do not provide any additional information. This will reduce Alarm rate significantly. Alternatively, Redundant alarms can also be grouped together into a single alarm group. Thus, reducing the overall alarm count significantly.

After analyzing the A&E log data from Water treatment plant in Singapore it was identified that Backwash Vent Level Switch Bad Value alarms in all the membrane trains always get triggered together with the Device failure alarm of the corresponding membrane train Backwash Vent level switch. For example, Backwash Vent Level Switch Bad Value alarm in Membrane Train 6 and the Device failure alarm in membrane train 6 Backwash Vent level switch always occur together exactly at the same time (See Figure 7 below). These two alarms are essentially the same alarms since both indicates about the malfunction/failure in backwash vent level switch. Hence, they are redundant alarms and one of this alarm can be suppressed or both these alarms can be grouped as one alarm. These two alarms contribute to about 5-6% of total alarm count. Therefore, suppression or grouping these alarms would result in about 3% reduction in overall alarm count.

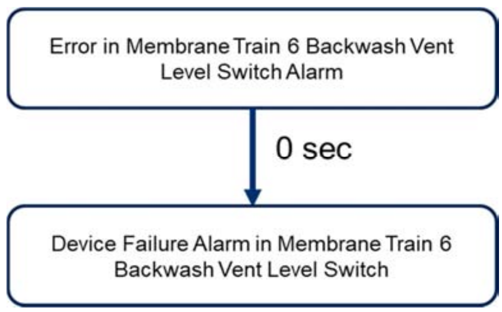

Figure 7. *An Example of Redundant Alarms.*

It was also identified through the Alarm Analysis that both Low warning and Low Alarm in all Lime silo levels always occur together at the same time (See Figure 8). Further investigation on these Lime silo level alarms reveals that the limits of both low warning and low alarms are the same in SCADA Alarm setting. Hence, Low warning and alarms limits are adjusted accordingly in SCADA in order avoid the activation of both low warning and low alarm together at the same time.

In our previous work [13], the proposed methodology presented in Figure 1 was applied on historical Alarm and Event log data from a petrochemical plant in Singapore to identify various interesting patterns such as – Alarm response patterns, redundant alarms, and consequential alarms. Several alarm rationalization activities such as Alarm Suppression or Alarm grouping or Alarm removal for redundant alarms, Alarm Prediction for consequential alarms, Standardization of Alarm response procedure were proposed in [13] based on the identified patterns of Alarm and Events.

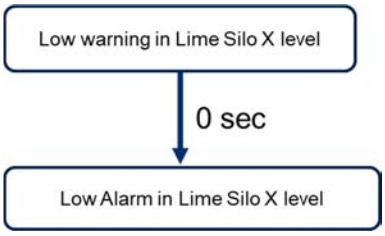

Figure 8. *An Example of Redundant Alarms.*

3. Conclusion

In this paper, we proposed a novel AI based method to systematically analyse large volume of Alarm and Event log data and applied it on the A&E log data from a water treatment plant in Singapore to extract many useful and important pattens of alarm and event sequences hidden in the data. The proposed methodology uses state of the art AI based techniques such as: association rule mining, text mining. Several actionable information can be derived from the extracted patterns. Various Alarm Rationalization activities (such as: Alarm suppression, alarm removal, modification of alarm configuration settings - changing the Alarm limits, hysteresis, delay timer settings) can also be performed based on the identified patterns of Alarms and events to improve the performance of alarm system by reducing the total alarm count. Apart from this, the extracted alarm patterns also provide valuable insight to the plant operators by identifying various Nuisance alarms (such as - Chattering Alarms, Redundant Alarms). The key benefits of the proposed method over the conventional association rule mining [14] and correlation analysis [15] based methods are: (i) the proposed method can identify the sequential patterns of alarm and events of longer duration (few hours or more) and provide the valuable time difference information between two consecutive alarms/events in the sequence along with the extracted sequence, which conventional methods cannot and furthermore (ii) it is computationally inexpensive (faster execution time), scalable and can be deployed in a big data framework. Currently, Research work is in progress and in future, we intend to perform Correlation analysis between Maintenance or Operation log with the Alarm & Event log to evaluate the effectiveness of the Maintenance or Operation Action. A given Maintenance or Operation Action can be ineffective if it does not result in resolving certain critical / bad actor alarms.

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