

ALAP: Alarm Prioritization System For Oil Refinery

Oi Mean Foong, Suziah Bt Sulaiman, Dayang Rohaya Bt Awang Rambli, and Noor Syazwani Bt Abdullah

Abstract— Alarm management is a fast-growing and important aspect in the oil refining process industries. While an alarm system functions as a tool to improve performance and monitor safety in a refinery plant, the alarm priority is used to convey the degree of seriousness of a specific alarm to operators. In this paper, we present a system prototype known as Alarm Prioritization (ALAP), which is developed using fuzzy logic, for Crude Distillation Unit (CDU) in an oil refinery. The objective of the paper is to prioritize the alarms during alarm floods which would ease the burden of operators with meaningless or false alarms. The ALAP prototype, which applies Mamdani inference engine, produces category and priority of the alarms that occur in the plant. The preliminary results have shown that the ALAP system helps the operators in deciding which critical alarms should be attended first rather than handling false or less priority alarms during the alarm floods.

Index Terms—Alarms floods, alarms prioritization, crude distillation unit, fuzzy logics, set points.

I. INTRODUCTION

In recent years, the oil refineries have been placing greater emphasis on improving their alarm management system to reduce the occurrence of accidents. It is understood that poor alarm systems will put thousands of lives at risk and contributes to major plant damage, production loss, environmental impact and also leads to losses of millions of dollars. Inadequate alarm systems are a crucial problem that gives big impact on other issues. The Abnormal Situation Management Team estimated that the United States of America petrochemical industry could save up to \$10 billions per annum from better management of alarms [1]. This explains the reason why alarm management system is becoming increasingly important.

Frequent alarms problems that encountered in the Distributed Control System (DCS) system are as follows:

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- There are many conflicting alarms that trigger at the same time for the operators to handle.
- The operators are at times heavily burdened with meaningless alarms that affect their time and performance.
- Major operating upsets generate alarm floods.

Although current process plants use in the DCS complies with the International Standard IEC 61508, yet the panel operators at the control rooms are often overwhelmed with too many alarms during plant upset. To address the problems, we propose and develop Alarm Prioritization System (ALAP) to calculate the severity of each alarm, categorize the alarms and rank the alarms based on its priority. With the help of automatic ALAP system, the panel operators could take the corrective and/or proactive measures quickly when alarms are triggered during alarm floods.

The rest of the paper is organized as follows: Section II surveys the related work on alarms management. Section III describes the methods used and the proposed system architecture of alarm prioritization. Section IV discusses the experimental results and analyses. Section V includes the system evaluation and lastly Section VI draws conclusions and suggestion for future work.

II. RELATED WORK

Effort in managing an alarm system for a controlled environment could be found as early as in the 1970s where automating the system was introduced. Various aspects of automation from different processing fields that include oil storage, refining, and oil compounding were reviewed and current trends in automation methods and hardware design were discussed. One key discussion point involved is the importance of having all processes connected to the central computer and integrated alarm system within the central control room could be obtained. The automation of alarm management system has now increased in its popularity as further improvement on the system is made by embedding an intelligent element into it [2], [3]. A large-scale semi-autonomous refinery robot, called AEGIS system, was developed to assist human operators in controlling refineries during abnormal situations such as when alarms occur [2]. The system has incorporated intelligent autonomous behavior and improved human situation awareness. Another intelligent example is reported in which an Intelligent Alarm Management System (IAMS) for suppressing nuisance alarms and providing information to help panel operators prioritize alarm information and take quick, correct action [3].

Similarly, an expert system for real-time fault diagnosis of complex chemical process is proposed [4]. The system is applied as a real-time computer aided decision support system, providing operation suggestions to help field operators when abnormal situation occurs.

One common theme from those works in developing an alarm management system is the emphasis on the criticality analysis that is on the prioritization of alarms [3]. The IAMS consists of a dedicated building block that handles an analysis whereby a criticality tag (very important, important, or less important) is assigned to each alarm message. Such a feature assists in informing operators which alarms are emergent or critical. On a similar focus, the system developed by Qian et al. provides the features that monitors the operation of process and infer the intellectual process of domain experts [4].

Many techniques and mechanisms have been adopted to develop expert systems especially in managing the alarms. Liu and Liu use the time series prediction in their work in which they extend two traditional classification techniques i.e. naïve Bayesian classifier and decision trees to suit temporal prediction [5].

III. METHODS

A. Current Alarm Management Systems

We had a field trip to an oil refinery plant in Malaysia for the purpose of understanding the current system and also to gather some data through the interview session with the operators. Based on the interview, the frequency of alarms in CDU is about 20 alarms in an hour which consists of high and low alarms. The operators need to be alerted every time the alarms are triggered because low priority alarms can turn into high priority alarms if they do not take appropriate actions within a few minutes. Emergency alarms should be taken seriously because the problems in one unit can propagate effect to another unit.

DCS is used to control and monitor the processes in the plant. There are several indicators for alarm criticality, i.e. sound and color. Sounds are different for each criticality of alarms. Based on sounds, the operators can easily identify the types of alarm that need to be taken into action. Another indicator is color which will determine the criticality of the process. For example, if the set point in DCS changes from green to red, it means the problem is very critical. The operators in the control room need to communicate with the field operators in the plant to confirm the problem before taking any action.

Some data were collected, which consisted of set points for each parameter, from the CDU. The alarms will be triggered if the parameter readings are either exceed or below the set points. Table 1 shows the details on each parameter's set points in several units. Since each unit has different set points, the setting for each DCS would also be different.

Table 1 Parameters that trigger alarms-warning

ALARM WARNING			
PARAMETERS	SET POINTS		UNITS
	Lower limits	Upper limits	
Temperature (°C)	135	140	Stabilizer
	75	80	CDU Overhead
	140	150	Hydrocracker unit
Pressure (kg/cm ²)	0.7	0.8	CDU Overhead
Level of Humidity (%)	40	55	CDU Overhead
	2	3	Hydrocracker unit

B. Process Flow of the Proposed System

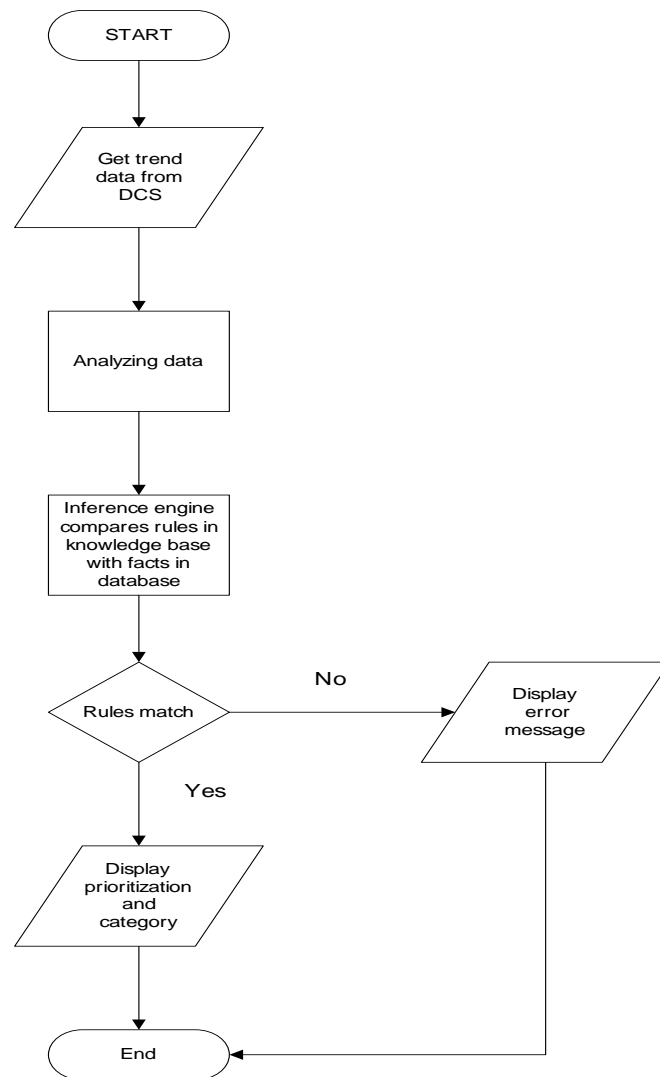


Fig.1 Flow chart of ALAP system

The flow chart of the ALAP system is described in Fig. 1. The system will get the trend data from DCS and analyze it. The inference engine will then compare the rules in knowledge base with data that is stored in the database as a fact. When the IF part of the rule matches a fact, the rule is fired and its THEN part is executed. The output will be sent to the operators through the graphical user interface. If rules do not match with the facts at all, the system will display error message and the operators need to identify it manually based on alarm sounds, color indicators and their experience.

C. Proposed System Architecture

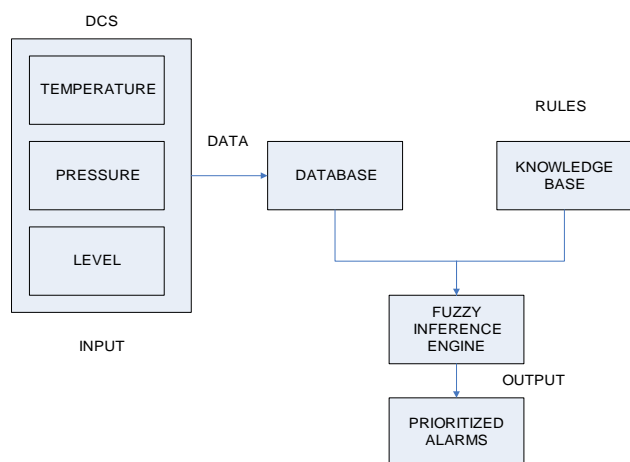


Fig. 2 System architecture of Alarm Prioritization (ALAP)

We propose the system architecture of Alarm Prioritization ALAP, as shown in Fig. 2. The input will be obtained from DCS which consists of temperature (°C), pressure (kg/cm²) and level of humidity (%). All these data will be stored in the database as facts that will be used to match with the IF part of the rules stored in the knowledge base. The knowledge base contains domain knowledge or rules for problem solving. The fuzzy inference engine will link the rules in knowledge base with the data in the database and perform the decision-making process. The alarms that have been prioritized will be displayed to the operators.

D. Fuzzy Logics and Membership Functions

According to Professor Lotfi Zadeh (1965), fuzzy logic is a set of mathematical principles for knowledge representation based on degrees of membership rather than on crisp membership of classical binary logic [6].

To facilitate in rules construction, five linguistic values, as shown in Table 2, are used to determine the ranges of the criticality for each parameter which are *low_low*, *low*, *normal*, *high* and *high_high*. These ranges of values are gathered from oil refinery engineers or experts. For the output, four different categories of alarms prioritization are used which are *normal*, *low*, *high* and *emergency*. In order to make sure that the results calculated using fuzzy logic are correct, each linguistic values has been assigned with a weight.

Table 2 Range for parameters' linguistic values

	Ranges				
	Low_low	Low	Normal	High	High_high
Temperature (°C)	<= 69.9	70.0 – 74.9	75.0 – 80.0	80.1 – 84.9	>= 85.0
Pressure (kg/cm ²)	<= 0.59	0.60 – 0.69	0.70 – 0.80	0.81 – 0.89	>= 0.90
Level of Humidity (%)	<= 34.9	35.0 – 39.9	40.0 – 55.0	55.1 – 59.9	>= 60.0

Table 3 Weights of linguistic values

Linguistic Values	Low_low	Low	Normal	High	High_high
Weight	3	1	0	2	3

The weights are assigned according to their priorities in Table 3. The weights for *low_low* and *high_high* are the same because both can lead to alarm trip or cause the system to shut down when no quick action is taken.

Table 4 Ranges for output

Output	Normal	Low	High	Emergency
Range	< 1.0	1.0 – 4.9	5.0 – 7.9	>= 8.0

The ranges, in Table 4, will be used to determine the output of different criticality of alarms for prioritization purpose.

The membership functions for temperature, as shown in Fig.3 below, are constructed using membership function editor in MATLAB. Similarly, the pressure and level of humidity parameters are constructed using membership function editor based on the ranges in Table 2. These membership functions have their own linguistic expressions which are used to describe the fuzzy sets.

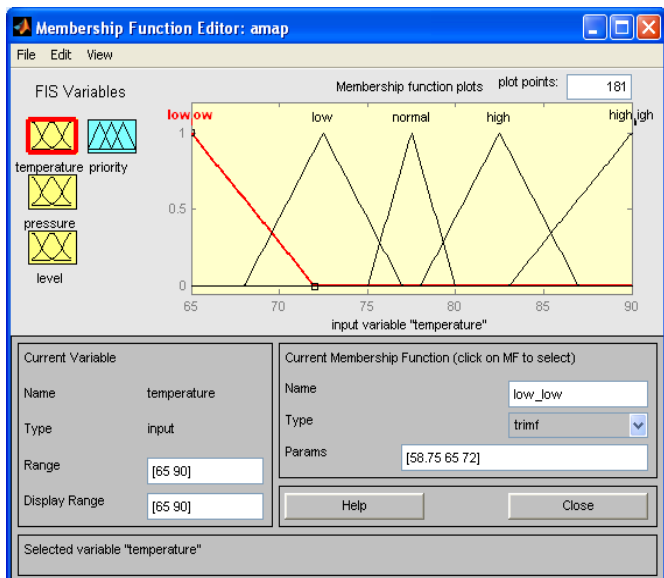


Fig. 3 Membership functions for temperature

The linguistic expressions for temperature parameter for all five linguistic values namely *low_low*, *low*, *normal*, *high* and *high_high* are shown in formula 1, formula 2, formula 3, formula 4 and formula 5 respectively:

$$\mu_{low_low}(t) = (72 - t) / 7 \text{ if } 68.0 \leq t \leq 72.0 \quad (1)$$

$$\mu_{low}(t) = \begin{cases} (t - 68) / 4.5 & \text{if } 68.0 \leq t \leq 72.5 \\ (77 - t) / 4.5 & \text{if } 72.5 \leq t \leq 77.0 \end{cases} \quad (2)$$

$$\mu_{normal}(t) = \begin{cases} (t - 75) / 2.5 & \text{if } 75.0 \leq t \leq 77.5 \\ (80 - t) / 2.5 & \text{if } 77.5 \leq t \leq 80.0 \end{cases} \quad (3)$$

$$\mu_{high}(t) = \begin{cases} (t - 78) / 4.5 & \text{if } 78.0 \leq t \leq 82.5 \\ (87 - t) / 4.5 & \text{if } 82.5 \leq t \leq 87.0 \end{cases} \quad (4)$$

$$\mu_{high_high}(t) = (t - 83) / 7 \text{ if } 83.0 \leq t \leq 90.0 \quad (5)$$

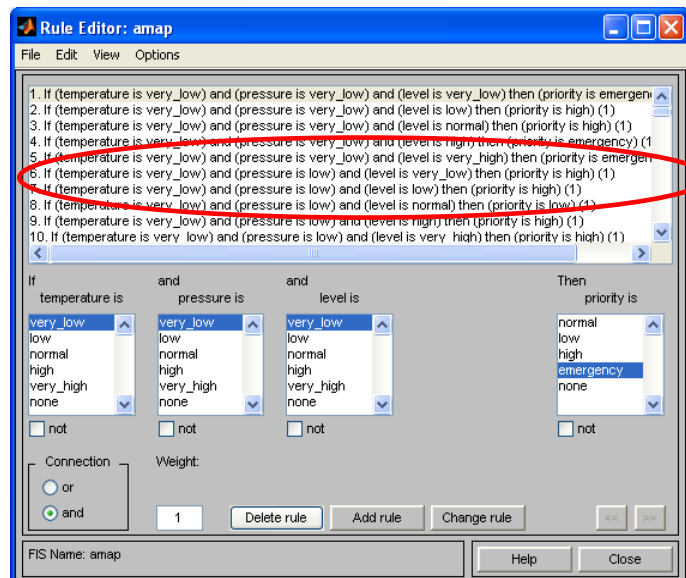
E. Fuzzy Rules

A total of 125 rules have been constructed so that each possible scenario can be matched with the correct rule. The fuzzy rules acquired from the experienced panel operators are shown in Fig. 4.

Rule 1: If (temperature is very low) AND (Pressure is very low) AND (Level of Humidity is very low) THEN Priority is Emergency.

Rule 2: If (temperature is very low) AND (Pressure is very low) AND (Level of Humidity is low) THEN Priority is High.

Rule 3: If (temperature is very low) AND (Pressure is very low) AND (Level of Humidity is normal) THEN Priority is High.



Rule 4: If (temperature is very low) AND (Pressure is low) AND (Level of Humidity is normal) THEN Priority is Low.

IV. EXPERIMENTAL RESULTS AND ANALYSES

With the help of Mamdani-style inference technique, crisp output is obtained by calculating the centre of gravity (COG) using formula 6 below:

$$COG = \frac{\int_a^b \mu_A(x) \cdot x \, dx}{\int_a^b \mu_A(x) \, dx} \quad (6)$$

A. Experimental Results

Fig. 5 shows the output of the system which helps the operators to make decision on which alarms to attend first if alarm flood occurs. For example, four alarms trigger at time 9.05 but with different priority which are “Low”, “High” and “Emergency”. So in this case, the operators should attend the emergency alarm first followed by high alarm and last is low alarm. They can identify which part of the CDU that has problem by looking at the tag number. They can also know which parameters that should be given higher attention by looking at the values that are displayed in the system or by checking it in the FIS Editor where all the set points have been set. If the alarms trigger at the same time and have same priority, operators can decide on which alarm to be attended first by referring to the crisp output in the “Priority” column. The priority values range from 0 to 10 with 10 ranked as the highest priority whereas 0 has the least priority.

Fig. 4 Fuzzy rules for ALAP system

Time	Tag	Temperature	Pressure	Level	Priority	Category
9.01	21101	70.94	0.581	36.99	6.34736	High
9.01	21179	70.36	0.781	55.67	4.08697	Low
9.01	21103	71.66	0.609	58.66	4.00894	Low
9.02	21112	89.61	0.584	39.18	6.5	High
9.03	21106	72.03	0.794	59.01	4.84506	Low
9.03	21161	72.54	0.799	43.97	2.9	Low
9.03	21160	84.72	0.912	49.88	5.45309	High
9.04	21104	71.01	0.772	33.08	3.58572	Low
9.04	21165	85.3	0.61	39.27	5	High
9.05	21108	90	0.583	64.01	8.82178	EMERGENCY
9.05	21109	75.5	0.76	40.1	2.87383	Low
9.05	21102	75	0.75	53.89	2.9	Low
9.05	21101	67.29	0.88	59.32	7.03815	High
9.06	21179	76.58	0.6	35.12	4.37766	Low
9.06	21108	79.65	0.576	41	4.41708	Low
9.07	21161	89.44	0.581	61.99	9.06585	EMERGENCY
9.08	21179	86.98	0.594	59.42	7.87918	High
9.08	21112	75.48	0.78	63.82	2.9	Low
9.09	21165	77.57	0.917	54.68	5.54701	High
9.09	21104	79.39	0.571	62	7.65206	High

Fig. 5 ALAP's output

For instance, two low priority alarms trigger at time 9.03 but different values are generated as shown in the 'Priority' column. So based on that column, the operators need to take action on the high priority alarm first instead of low priority alarm.

Time	Tag Ilo	Temperature (°C)	Pressure (kg/cm²)	Level (%)	Priority	Category
9.07	21161	89.44	0.581	61.99	9.06585034	EMERGENCY
9.05	21108	90	0.583	64.01	8.821782178	EMERGENCY
9.08	21179	86.98	0.594	59.42	7.879175232	High
9.09	21104	79.39	0.571	62	7.652063496	High
9.05	21101	67.29	0.88	59.32	7.038153425	High
9.02	21112	89.61	0.584	39.18	6.5	High
9.01	21101	70.94	0.581	36.99	6.347361885	High
9.09	21165	77.57	0.917	54.68	5.547006063	High
9.03	21160	84.72	0.912	49.88	5.453091055	High
9.04	21165	85.3	0.61	39.27	5	High
9.03	21106	72.03	0.794	59.01	4.845057984	Low
9.06	21108	79.65	0.576	41	4.417078117	Low
9.06	21179	76.58	0.6	35.12	4.377663204	Low
9.01	21179	70.36	0.781	55.67	4.08697229	Low
9.01	21103	71.66	0.609	58.66	4.008939362	Low
9.04	21104	71.01	0.772	33.08	3.585724968	Low
9.03	21161	72.54	0.799	43.97	2.9	Low
9.05	21102	75	0.75	53.89	2.9	Low
9.08	21112	75.48	0.78	63.82	2.9	Low
9.05	21109	75.5	0.76	40.1	2.873829935	Low

Sort Data

Fig. 6 Prioritized Alarms and Category

After calculating the priority values for all alarms, we rank the alarms in accordance to the severity of alarms by sorting the numerical values in descending order, as indicated in Fig. 6. Thus, the operators would be relieved of the burden of making inappropriate decisions whenever alarm floods occur.

V. SYSTEM EVALUATION

System Evaluation is performed by conducting usability testing followed by benchmarking with the industry best practice alarms [7], [8], [9].

A. Usability Testing

System testing is done in order to verify the reliability and accuracy of ALAP. This system was tested and evaluated by two panel operators, four process control engineers and a chemical engineer expert who had been trained in process control in oil refinery plant. The experimental results are tabulated in Table 5. A set of questionnaires has been created and the system is evaluated based on Likert Scale. The scales used for the usability testing are as below:

- 1 – Strongly disagree
- 2 – Disagree
- 3 – Neither agree nor disagree
- 4 – Agree
- 5 – Strongly agree

Table 5 Results of Usability Testing

Questions	Scale		Average Scale
	Operator s	Engineers	
Is the system user-friendly and easy to use?	3.5	3.4	3.45
Are the results produce by ALAP understandable?	4	3.8	3.90
Is ALAP helpful in assisting me to quickly identify alarm's priority?	4	3.0	3.50
Are the rules used in ALAP appropriate and correct?	3	2.6	2.80
	Average		3.41

Preliminary results from the usability testing have indicated that ALAP is a useful tool in prioritizing the alarms, with an average score of 3.4 out of 5.0, which would lead to reducing the time taken by the operators to check and confirm each alarm before taking any corrective action.

B. Benchmarking with Industry Standard

Comparison is done by taking actual results from ALAP and comparing it with best practice alarms [10]. By comparing the results, the frequency of alarms that occur during alarm floods can be identified and measured so that it can be used as a benchmark for the oil refinery to manage their alarms more efficiently. Fig. 7 shows the comparison between actual alarms and best practice alarms. The frequency alarms, specifically high and emergency alarms, taken from ALAP are higher than those best practice alarms which means the alarms in CDU still need to be well-managed so that they can comply with the industry standard practice. It is important because high frequency of critical alarms will give rise to many undesirable effects to the plant's performance and the processes involved.

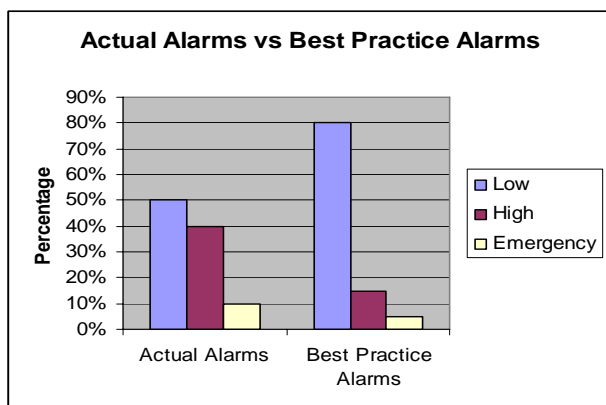


Fig.7 Benchmarking of ALAP's actual alarms and industry best practice alarms

VI. CONCLUSION

The uncertainty of determining the alarms categories can be resolved as the ALAP system helps operators to give more attention on the most important alarms rather than wasting time attending to false or less priority alarms especially during the alarm floods. It will be good to implement ALAP in oil refinery as it will enhance the safety of plants and can also increase the productivity of the operators. This is because they will not be burdened with meaningless alarms and can quickly identify emergency alarms during alarm floods. ALAP can be used as a tool to supplement the current system in the oil refinery. Both systems can coexist together and provide greater benefits to the operators as well as to the plant's safety.

Future work will include adopting hybrid technique in real-time alarm management. Besides reducing the uncertainty of alarms, the ALAP prototype will be further enhanced using iterative approach so that it would serve as complementary plug-in tool to its existing system for the oil refinery. By then, it will have the capabilities of self-learning and self-tuning which means the prototype system can perform automatic diagnostics of the alarms patterns in the near future.

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