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A FUZZY CRITICALITY ASSESSMENT SYSTEM OF PROCESS EQUIPMENT FOR OPTIMIZED MAINTENANCE MANAGEMENT

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ABSTRACT

In modern chemical plants it is essential to establish an effective maintenance strategy, which will deliver financially driven results at optimized conditions, i.e. minimum cost and time by means of a criticality review of the equipments in maintenance. In this paper a fuzzy logic based criticality assessment system of a local company's equipments is introduced. This fuzzy system is shown to improve the conventional crisp criticality assessment system. Results from case studies show that the fuzzy logic based system can perform the analysis same as the conventional crisp system can do; and in addition, it can outperform, e.g. outputs more criticality classifications with improved reliability and a greater number of different ratings that account for fuzziness.

KEYWORDS

Equipment criticality assessment, Maintenance management, Fuzzy logic

1. INTRODUCTION

In modern chemical plants, it is essential to establish an effective maintenance strategy. Criticality-based maintenance (CBM) is a prioritized approach to the maintenance of process equipments in the chemical process industries (CPI). In a process and hazard criticality ranking (PHCR) study, each equipment item is evaluated with a 'what if it fails' scenario. This requires personnel with thorough knowledge of the process/equipment under study. The PHCR value is a relative ranking in an overall criticality hierarchy that is used to determine priorities for maintenance programs, inspections and repairs (Ciliberti V Anthony, 1998). A decision making support systems of this kind, which can achieve expert-level competence in solving problems in task areas by gathering a body of knowledge about sepecific functions, is called knowledge-based or expert systems. More often, the two terms, expert systems (ES) and knowledge-based system (KBS) are used synonymously (Fasanghari, M. and Montazer, G.A., 2010).

In this paper a crisp criticality assessment system (CCAS) currently used in a local chemical company based in West-Yorkshire UK, is presented (Jani M. B., 2004). The vagueness of the system was discovered during implementation of the system. To improve the system's robustness, fuzzy logic is applied to the CCAS system and consequently a fuzzy criticality assessment system (FCAS) is developed. Finally the advantages of the new FCAS system over the existing CCAS system are demonstrated with some real cases.

2. CRITICALITY ASSESSMENT SYSTEM (CAS) AND EXPERT SYSTEM (ES) IN DECISION MAKING

2.1. CRITICALITY ASSESSMENT REVIEW

Criticality assessment review of equipments provides the structure around which a chemical plant can form its operational maintenance plan. The review is to assess the process criticality for individual equipment items, taking into consideration the potential impact upon the Environment and Health & Safety, and the financial impact upon the business in the event of equipment failure (Dekker R. et al., 1998; Lee J. and Hong Y., 2003). Normally a Multi-Criterion Classification of the Critical Equipment (MCCCE) technique, as defined by Felix et al. (2006), is used in a criticality review and assessment. Through the criticality review and assessment, companies can achieve:

- a proper preventive maintenance for safer equipment, better equipment availability for production, and lower maintenance costs;
- active planning, forecasting, scheduling and follow-up of most work with minimum downtime and need for emergency repairs;
- an accurate and complete recording of equipment maintenance activities and their associated costs (material and labour), which provides the necessary maintenance data for maintenance managers to analyse and control maintenance costs.

Afefy H. Islam (2010) reported that by implement of the equipments criticality assessment for the plant components, about 22.17% of the annual spare parts cost are saved as the result of the preventive maintenance.

2.2. CRITICALITY ASSESSMENT SYSTEM USED AT THE LOCAL CHEMICAL COMPANY

Criticality assessment review of the equipments at the local chemical company, in West-Yorkshire UK, was carried out during 2003-2004 (Jani M. B., 2004). The review looked at all the plant equipment in considerable detail, down to instrument level. The assessment method in use was based upon a corporate procedure as shown in Figure-1, and several tasks were conducted through the review, such as collecting and reviewing equipment criticality data; concurrently building and collecting data for critical spares.

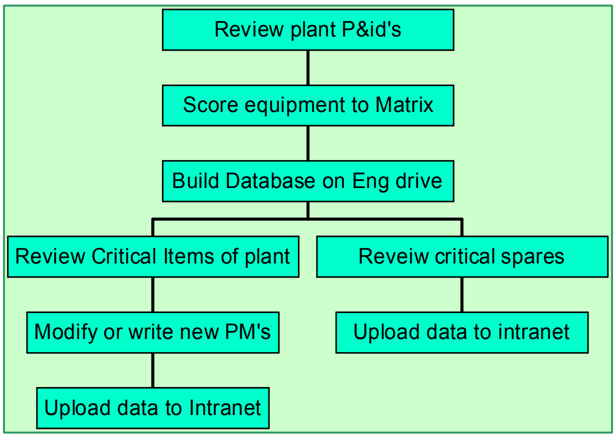

Figure 1 –Flow chart map of criticality assessment procedure (Jani M. B., 2004)

The assessment method was based on a corporate procedure for criticality assessment and involved looking at the primary function of an item and establishing the consequences of loss of its function with the three factors/features listed in Table-1.

Table 1- Three factors for the criticality assessment

1.	Environment, Health and Safety (EHS)
2.	Impact on Business (IoB)
3.	Annual Maintenance Cost (AMC)

This procedure was applied to all facilities, structures, systems, equipment (rotating or fixed), and components in the plant, including electrical, mechanical and instrumentation. All equipment within the plant were evaluated and processed through the criticality assessment process based upon site experience and team knowledge represented by a 'Team of Plant Experts' (TPES).

2.2.1. Team of Plant Experts (TPES)

The Team of Plant Experts was a group of staff in the company with a good mix of expertise of knowledge of the production process, the environment (e.g. discharge of contents in air and waste water and other regulations), as well as maintenance/operation of the plant. The team members, normally 8 to 10 staff at the plant site depending upon the area of operation being considered, included the Operational Supervisor, Operator, Safety/EHS Representative, Area Engineer, Process Engineer, Production representative, Shift manager, Maintenance Supervisor/Manager/representative, and Technical representative.

The potential effect of each asset on each of the three aforementioned aspects (shown in Table-1) in the case of its failure was determined by TPES. The most probable failure situation associated with each of the assets, among a number of failure scenarios, was determined by TPES in terms of level of impact of the failure on the company as far as maintenance was concerned. Crisp scores (0, 1, 2, 3 or 4) were assigned by TPES to each of the assets with regard to effect on EHS, IoB and AMC (see Table-1).

2.2.2. Structure of the Crisp Criticality Assessment System (CCAS)

The structure of CCAS is illustrated in Figure-2, which consists of three inputs and two outputs. Input One is the Effect on Environment, Health and Safety (EHS). The score of EHS for each of the assets, assigned by TPES based upon its hazardous extent, could be 0, 1, 2, 3 or 4, as shown in Table-2. Input Two is the Effect of Impact upon Business (IoB). The score of IoB for each of the assets, assigned by TPES based on the business loss if shutdown of whole unit for certain time, could be 0, 1, 2, 3 or 4, as shown in Table-3. Input Three is the Effect upon Annual Maintenance Cost (AMC). The score of AMC for each of the assets, assigned by TPES based on the equivalent cost of maintenance, could be 0, 1, 2, 3 or 4, as shown in Table-4.

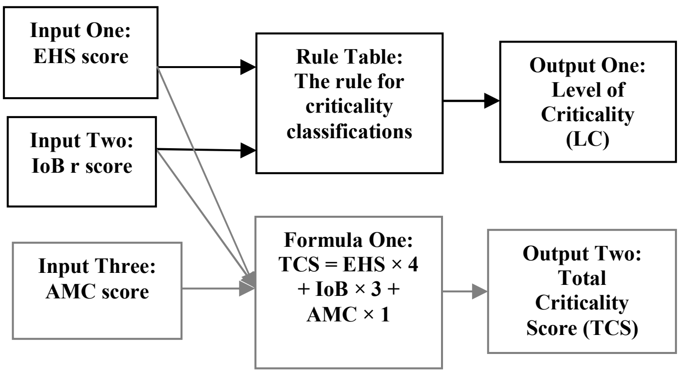

Figure 2 –Structure of the Crisp Criticality Assessment System (CCAS)

Based on Input One and Input Two, the system provided the level of criticality (LC) as Output One for each of the assets shown in Figure-2. The LC was decided using a rule table (see Table-5) designed by TPES. The LC of each of assets was classified as HIGH (score 2) or MEDIUM (score 1) or LOW (score 0) according to its scores on EHS and IoB. As a result, all assets were grouped in three categories (i.e. Low, Medium and High) based on the LC score. The decision on maintenance priority for individual asset was based on the category of the asset.

Input Three, i.e. AMC score, did not actually have any effect as far as the LC classification was concerned. However, it did play a role in determining the total criticality score (TCS) for each asset, which was Output Two of the CCAS, as shown in Figure-2. The TCS score was derived based on the following Formula:

$$TCS = EHS \times 4 + IOB \times 3 + AMC \times 1 \qquad (1)$$

4, 3 and 1 are weight factors assigned by TPES for the three inputs, respectively, reflecting the level of influence of each input on the total criticality score (TCS). EHS (with weight factor 4) has higher effect on TCS, as well as on LC, than IoB (with weight factor 3). The AMC (with weight factor 1) has the least effect on TCS and has no effect on LC. For some other companies, the third input may be become influential, and the weight factor should be considered differently (consequently the third input may not be ignored as far as LC is concerned). The company used TCS, which varies from zero to a maximum of 32 (based on the Formula-1), to differentiate the relative criticality of individual asset within the same LC category whenever necessary. As the company used only the first two inputs to decide the level of criticality (LC), this paper only considers the first two inputs.

Table 2- HAZARD impact

Effect on EHS	Description	Score
Not Hazardous (NH)	No hazards* exist	0
Slightly Hazardous (SH)	Potential First Aid injury on site Non-regulated release could occur Local order	1
Hazardous (H)	Potential OII*, LT1* on site Regulated release exceeding permit conditions could occur Offsite odour complaint	2
Extremely Hazardous (EH)	Potential serious permanent injury on site Potential offsite injuries (FA*) Regulated release occurs causing local environmental damage Multiple offsite odour complaints Local media coverage	3
Deadly Hazardous (DH)	Potential loss of life on site Potential serious offsite injuries (OII+) Regulated release occurs causing long term environmental damage National media coverage.	4
*Notes: the corresponding definition/description for Hazard, OII, LT1and FA can be found in ref. (Jani M. B., 2004)		

Table 3- BUSINESS impact

Effect on IoB	Description	Score
No effect (NE)	No impact on production	0
Less effect (LE)	Shutdown for up to 1 hr. (It is equivalent to business loss of up to £5000)	1
Medium effect (ME)	Shutdown for1-8 hrs. (It is equivalent to £5000 -£50000 business loss)	2
High effect (HE)	Shutdown for 8-24 hrs. (It is equivalent to £50,000-£100,000 business loss)	3
Very high effect (VE)	Shutdown for more than 24 hrs. (it is equivalent to more than £100,000 loss)	4

Table 4- MAINTENANCE impact

Effect on AMC	Description	Score
Very Low (VL)	< £1,000 per year	0
Low (L)	£1,000 - £10,000 per year	1
Medium(M)	£10,000- £20,000 per year	2
High (H)	£20,000 - £50,000 per year	3
Very High (VH)	> £50,000 per year	4

Table 5- Rule table for Level of Criticality (LC) score

EHS / IoB	0	1	2	3	4
0	LOW (0)	LOW (0)	LOW (0)	MEDIUM (1)	HIGH (2)
1	LOW (0)	LOW (0)	LOW (0)	MEDIUM (1)	HIGH (2)
2	LOW (0)	LOW (0)	MEDIUM (1)	MEDIUM (1)	HIGH (2)
3	LOW (0)	MEDIUM (1)	MEDIUM (1)	HIGH (2)	HIGH (2)
4	LOW (0)	MEDIUM (1)	HIGH (2)	HIGH (2)	HIGH (2)

2.2.3. Necessity for system improvement

Advantages of CCAS The CCAS was run successfully at the company. By using the CCAS, the company assessed all equipment, as shown in Figure-3, where 17.9 % of them were in the High category, 26.8% were in the Medium category and 55.3% belonged to the Lower category (Jani M. B., 2004). The Criticality Assessments were recorded in an Excel spreadsheet, allowing easy manipulation and sorting of data. This spreadsheet became a control document with an appropriate change and control procedure. New equipment was assessed and added to the list when it was installed.

The benefits of implementing the CCAS at the company's West-Yorkshire plant include:

- Reducing the risk of serious failures on high criticality assets;
- Reducing costs by reduced labour requirement (as 'low criticality' assets require less attention);
- Reducing usage of parts due to unnecessary maintenance;
- Reducing planned maintenance stoppages due to unnecessary maintenance;
- High productivity attributed to 'critical assets' improved reliability.

Utilisation of the CCAS can minimise unplanned event such as:

- Injury to people, both employees and the public;
- Damage to the environment;
- Loss of process material;
- Damage to capital assets;
- Increase of operating costs.

In addition, the CCAS is easy to use and it is easy to update the assessment score with new inputs of the company's assets.

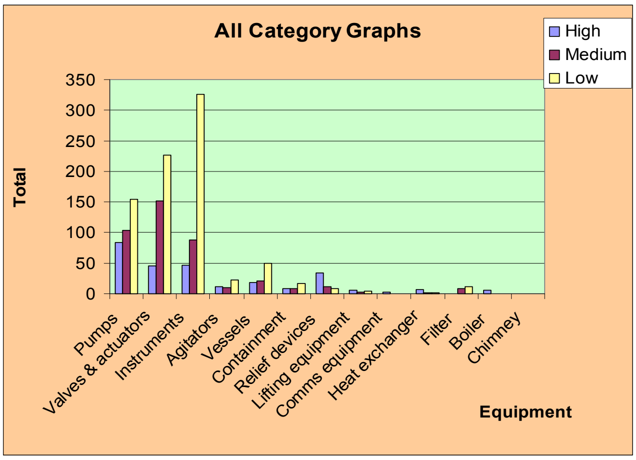

Figure 3 –All Categories Critical Equipment Chart (Jani M. B., 2004)

Issues for improvement To evaluate the system performance, three issues have been identified:

1, The input The input scores for HES and IoB are simple, but have some drawbacks. For instance, when TPES evaluates an individual asset, it is likely they may have different views on what scores for HES (and IoB) should be assigned. The CCAS cannot accommodate these differences. For example, during the critical assessment of an agitator motor, which was used in the Effluent Plant to give motion to an agitator, the TPES demonstrated some differences in opinion on the EHS score for the agitator motor. In the TPES with 10 members, 5 members gave a score of 0 and the other 5 members gave a score of 1. In the CCAS, however, TPES had to agree on what score (with an integer value) should be assigned. Then, eventually, everybody agreed on a score of 1. Such rigidity of the CCAS on input information might filter out some useful information, i.e. differences in TPES' opinions might indicate that the actual score should be assigned with some degree of uncertainty/fuzziness, e.g. a possibility of a score lying between 0 and 1. As far as the IoB score is concerned, apart from no tolerance on the difference among TPES' opinions (the same as on EHS score), the CCAS treats, for example, a loss of £5000 and a loss of £50000 the same as they both score 2 (see Table-3). It would be better if a system could take the actual estimated value as the input.

2, The output The output score on the level of criticality is an integer score of 0, 1 and 2 that represent Low, Middle and High, respectively.

It is known that the company also wanted to rank assets within the same level of criticality group in terms of importance to the production operation, which was one of the reasons that the third input, AMC, was included in the CCAS. It would be better if the input information, in terms of EHS and IoB, could be used not only to assess individual asset to different levels of criticality but also to rank the assets within each level of criticality group.

3, The rule set The rule set in Table-5 set up by TPES is the core of the CCAS. Robustness of the rules used affects the quality of the criticality of assessment. The 25 rules, generally speaking, represent the knowledge of the team of experts (i.e. TPES) and are reliable. However, it is possible that human error and uncertainty existed in the determination of the 25 rules that might make some of the rules less trustworthy and rather subjective. So it is necessary to evaluate and fine tune the rules to make them better in representing the logic of the physical system.

The issues mentioned above can be addressed naturally by integrating the functions of Fuzzy logic inference engines and fuzzy membership into the CCAS.

2.3. FUZZY EXPERT SYSTEM

The quality of decisions, in terms of repair priorities and resource assignment, is the critical factor for a production company. A decision support system plays a vital role in the decision process enhancement. One problem in a decision process is how to deal with or represent the meaning of vague concepts usually used in situation characterization, such as those implicit in linguistic expressions like 'very hazardous', 'very expensive to repair'. One possible approach to handle vague concepts is Fuzzy Set Theory, formulated and developed around 50 years ago by Lotfi Zadeh (1977). Fuzzy set theory is a generalization of classical set theory that provides a way to absorb the uncertainty inherent to phenomena whose information is vague and supply a strict mathematical framework, which allows its study with some precision and accuracy. A fuzzy set presents a boundary with a gradual contour, by contrast with classical set, which present a discrete border. Since fuzzy logic can be easily adopted as a means of both capturing human expertise and dealing with uncertainty, fuzzy systems have been successfully applied to various applications and large-scale complex systems that exist everywhere in our society (Yager R. R., 1980; Zimmermann H. J., 1992; Zadeh L. A., 1996; Betroluzza C., et al., 1995; Garavelli A. C., 1999; Tran L. T. and L Duckstein., 2002; Buyukozkan G., and Feyzioglu O., 2004; Lu K. Y. and Sy C. C., 2009). Fuzzy expert system has been developed in decisions involving uncertainty and ambiguity (Tran L. T. and L Duckstein., 2002), where fuzzy logic enables expert system (ES) in coping with uncertainty and in dealing with both quantitive and qualitive variables. Buyukozkan G., and Feyzioglu O., (2004) pointed out that fuzzy logic decision systems can encode expert knowledge in a direct and easy way using rules with linguistic labels. The main tasks in developing the fuzzy logic decision system consists of determining membership functions, fuzzy rules, fuzzification and defuzzification. The membership functions and fuzzy rules are generated by best representing the company's expert knowledge.

3. DEVELOPMENT OF A FUZZY CRITICALITY ASSESSMENT SYSTEM (FCAS)

3.1. FCAS SET-UP FOR LEVEL OF CRITICALITY ASSESSMENT

To keep a same system structure, the new FCAS used the EHS and IoB as two fuzzy inputs for the assessment of level of criticality (LC). The structure of the FCAS system is illustrated in Figure-4 (Alzaabi R. N., 2005).

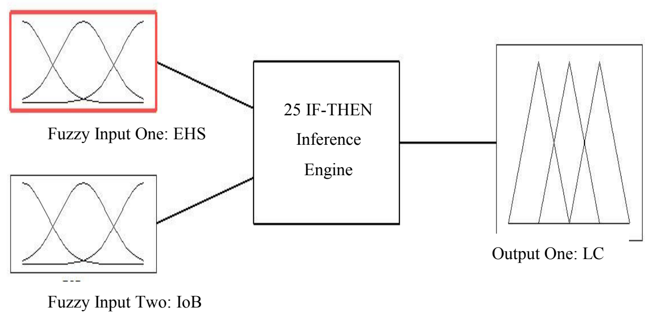

Figure 4 –Structure of the Fuzzy Criticality Assessment System (FCAS)

The FCAS consists of two fuzzy events as the system inputs (i.e. EHS and IoB), one inference engine based on 25 IF-THEN rules using the Mamdani method, and one crisp output through de-fuzzyfication with Centroid method (Mamdani E. H., 1977).

3.1.1. Two fuzzy inputs: EHS and IoB

Each crisp-input of the previous CCAS system is replaced by corresponding fuzzy input with fuzzy membership functions, as shown in Figure-5 and Figure-6. Five fuzzy labels are assigned for each input, as shown in the right-hand column in Table-6 for EHS and Table-7 for IoB. EHS as antecedent 1 has five labels, i.e. NH, SH, H, EH, DH. IoB as antecedent 2 has five labels, i.e. NE, LE, ME, HE, VE. For comparison, the scores in the left-hand column of the tables are those used in CCAS system.

Table 6- Fuzzy labels for EHS

Score	Effect on EHS	Fuzzy Labels
0	Not Hazardous	NH
1	Slightly Hazardous	SH
2	Hazardous	H
3	Extremely Hazardous	EH
4	Deadly Hazardous	DH

Table 7- Fuzzy labels for IoB

Score	Effect on IoB	Fuzzy Labels
0	No effect on production	NE
1	Shutdown of whole unit for up to 1 hr. (It is equivalent to loss of up to £5000)	LE
2	Shutdown for1-8 hrs. (It is equivalent to £5000 -£50000 loss)	ME
3	Shutdown for 8-24 hrs. (It is equivalent to £50,000-£100,000 loss)	HE
4	Shutdown for more than 24 hrs. (it is equivalent to more than £100,000 loss)	VE

The membership function for EHS is established to give numerical meaning to each label as shown Figure-5. A triangular membership function is used. EHS is assumed within a universe of discourse $U_1 = \{EHS \ / \ 0 \leq EHS \leq 4\}$. Therefore, we use a limited universe of discourse to the range of interest of application for EHS. The lower boundary is zero. This makes sense because it means no hazardous effect on production. This also is identical with the set up of the existing crisp system (CCAS).

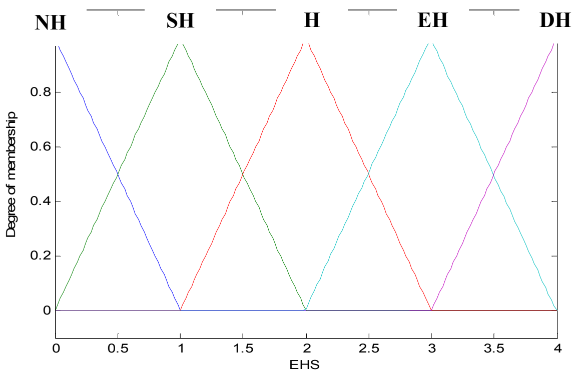

Figure 5 –EHS membership functions

The membership function for IoB is established to give numerical meaning to each label as shown Figure-6. A trapotropical membership function is used. IoB is assumed within a universe of discourse $U_2 = \{IoB \ / \ 0 \leq IoB \leq \infty\}$. Therefore, we use an unlimited universe of discourse to the range of interest of application for IoB. The lower boundary is zero. This makes sense because it means no effect on production or shutdown of the whole unit for zero hour and equivalent to business loss of £0. This also is identical with the set up of the existing crisp system (CCAS).

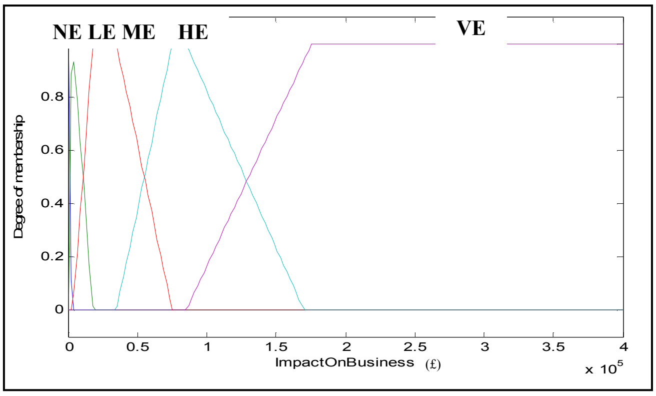

Figure 6 –IoB membership functions

Table 8- Fuzzy labels for LC

Crisp Score	Fuzzy Score	Level of Criticality	Fuzzy Labels
0	≤0.5	LOW	L
1	0.5< ≤1.5	MEDIUM	M
2	1.5< ≤2.5	HIGH	H
3	2.5<	VERY HIGH	VH

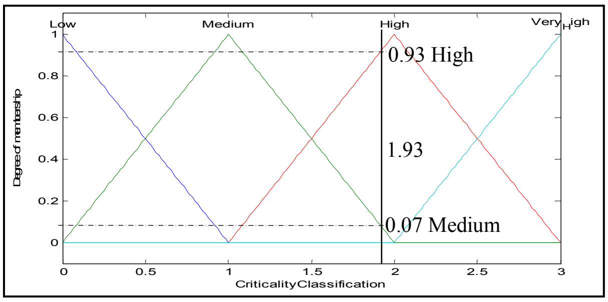

Figure 7–Criticality classification membership functions

3.1.2. The output: Level of Criticality (LC)

Four fuzzy labels, i.e. L (Low), M (Medium), H (High) and VH (Very High), are assigned for Level of Criticality (LC), as shown in the right-hand column in Table-8. For comparison, the left-hand column of the table is the Level of Criticality scores assigned by TPES used in CCAS.

The membership function for LC is established to give numerical meaning to each label. Triangular membership function is used for LC as shown in Figure-7. The universe of discourse of LC as the consequent in the rule-based fuzzy logic approach is $U_3 = \{LC \ / \ 0 \leq LC \leq 3\}$. We use a limited universe of discourse to the range of interest of application for LC. This also is identical with the set up of the existing crisp system (CCAS).

3.1.3. IF-THEN rule-base

IF-THEN rules have been set up for the fuzzy inference, which can be presented in a matrix form, referred to as a Fuzzy Associative Memory (FAM), which has a similar form as the rule table in Table-5 used in CCAS. FAM is a matrix that uses the labels of one input for the row names and the labels of another input variable for the column names. Each cell in the matrix contains an output label denoting the output resulting from a specific input combination represented by the row and column (Buyukozkan G., and Feyzioglu O., 2004). For the FCAS, using EHS and IoB as the inputs and LC as the output, the FAM is developed to generate fuzzy output as given in Table-9. Since the five labels are defined for each input, the FAM is a 5×5 matrix. 24 of the 25 rules in the rule matrix in Table-9 are identical with the rules designed by TPES in the CCAS (see Table-5). One new rule, i.e. 'If EHS is DH and IoB is VE, then LC is VH', is introduced for the FCAS. (In comparison, in company's CCAS system, 2 (=HIGH) is the output when EHS and IoB both score 4.)

Table 9- Fuzzy Associative Memory (FAM) matrix for criticality classifications

EHS / *IoB*	*NH*	*SH*	*H*	*EH*	*DH*
NE	L	L	L	M	H
LE	L	L	L	M	H
ME	L	L	M	M	H
HE	L	M	M	H	H
VE	L	M	H	H	(VH)

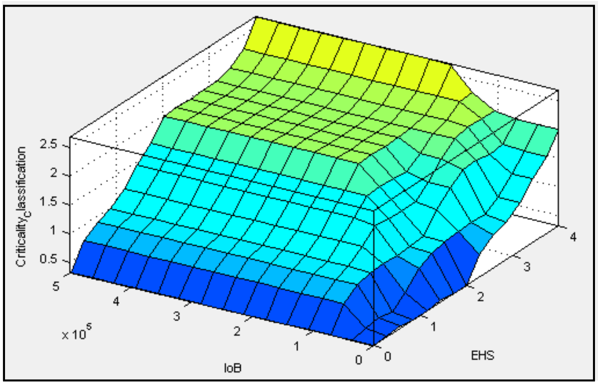

Figure 8–The profile of the fuzzy inference representing the 25 IF-THEN rules used in the FCAS

The input variables appear only in the antecedent part (i.e. IF part) of fuzzy rules, while the output variable is found only in the consequent part (i.e. THEN part) of fuzzy rules. For example, 'If EHS is EH and IoB is LE, THEN LC is M'. Figure-8 shows the profile of the fuzzy inference based on the Mamdani method using the Matlab Fuzzy Logic Tool Box, to represent the 25 IF-THEN rules of the FACS system in Table-9. The profile shows a transit of the level of criticality from 0 to 3 in representing LOW, MEDIUM, HIGH and VERY HIGH respectively. It also indicates from the profile that EHS is superior to IoB in terms of effect on LC, which was implemented in the company's CCAS. The profile shows that the 'IF-THEN' inference engine in the FCAS truly represents the company's experts (TPES) opinions and knowledge.

3.1.4. De-fuzzification and crisp output for the LC

The LC score for each of the assets (i.e. LOW, MEDIUM, HIGH, and VERY HIGH) is obtained through aggregation and de-fuzzification. 'Min-Max' inference is used in rule evaluation. It takes the minimum of the antecedents and the maximum of the rule strengths for the consequent. The Centroid method is used for de-fuzzification. The final level of criticality (LC) for each asset is one of the four categories (from L to VH) based on the fuzzy set definition of LC shown in Table-8.

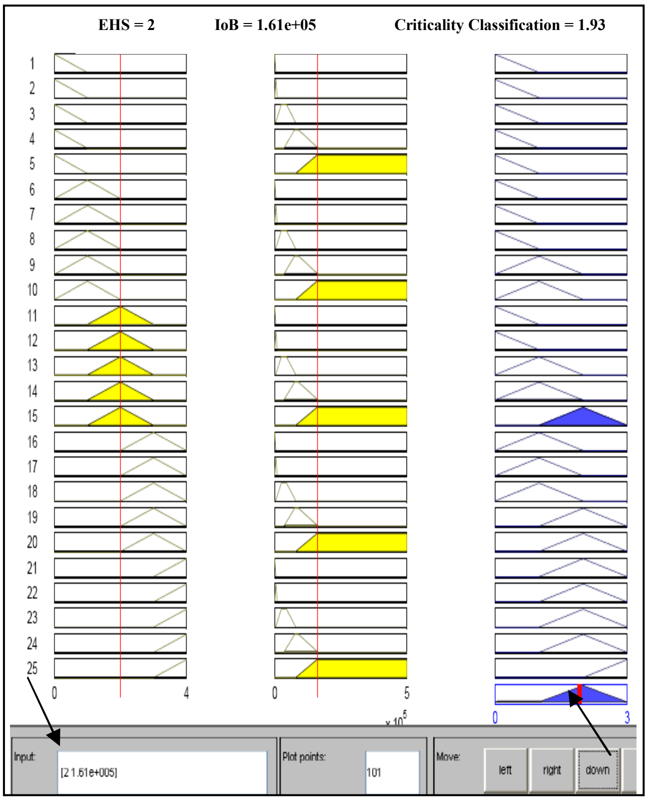

Figure 9 –Inputs and Output

Figure-9 demonstrates how output is obtained when the EHS and IoB are entered. The left-down arrow in the figure shows the container where the inputs are entered (EHS = 2 and IoB = £161,000). In the fuzzy inference process, the input of EHS fires the rules from eleven to fifteen, as shown in the left column. Meanwhile, the input of IoB fires the rules of five, ten, fifteen, twenty, and twenty five respectively and simultaneously, as shown in the middle column. The result of Criticality Classification then appears on the place where the right-up arrow pointing, and the value 1.93 is the result obtained from the fuzzy inference. Based on

Table-8, the asset is classified as level 2 (or HIGH) in terms of level of criticality (as 1.5 < 1.93 < 2.5), which is same as the result obtained from the case company's current CCAS. Based on the definition of the Criticality classification membership functions (see Figure-7), the score of 1.93 can be interpreted as: the corresponding asset is of 93% level 2 (or HIGH) and 7% Level 1 (or MEDIUM), as indicated in Figure-7. For further comparison of two systems (i.e. FCAS and CCAS) 6 cases are closely studied, which are summarised in Table-10.

4. RESULTS AND DISCUSSIONS WITH CASES STUDY

4.1. CASES STUDY

The powerfulness and robustness of the fuzzy criticality assessment system (FCAS) can be noticed by looking and noting the differences between the CCAS and the FCAS shown in Table-10, which includes critical assessments of 6 assets. The Colum 3 and Colum 4 in Table-10 are the two inputs, EHS and IoB. For CCAS the two inputs are integers. For FCAS, however, the input of IoB is the real value (i.e. equivalent number of hours lost and corresponding business loss in £) and the input of EHS is a statistical average of the collective scores from individual member of the TPES. The Colum 5 includes the outputs obtained from both CCAS and FCAS.

Table 10- Comparison of FCAS with CCAS

Asset No.		**INPUT ONE: EHS**	**INPUT TWO: IoB**	**OUTPUT : LC**
1	Crisp	3	4	2 = H
	Fuzzy	3.5 = (4*3+3*3+3.5*2)/8	36hrs (~£200,000)	2.4 = H (0.4VH, 0.6H)
2	Crisp	3	4	2 = H
	Fuzzy	3.375 = (4*3+3*5)/8	24hrs (~£100,000)	2.2 = H (0.2VH, 0.8H)
3	Crisp	3	2	1 = M
	Fuzzy	2.5 = (3*3+2*3+2.5*2)/8	4 hrs (~£25,000)	1.2 = M (0.2H, 0.8M)
4	Crisp	2	2	1 = M
	Fuzzy	1.4 = (2*4+1*6)/10	6hrs (~£35,000)	0.7 = M (0.7M, 0.3L)
5	Crisp	1	1	0 = L
	Fuzzy	0.5 = (1*5+0*5)/10	0.5hr (~£2,500)	0.4 = L (0.4M, 0.6L)
6	Crisp	0	0	0 = L
	Fuzzy	0.4375 = (1*3+0*4+0.5*1)/8	0hr (~£0)	0.3 = L (0.3M, 0.7L)

Taking the third case in Table-10 as an example, where the asset score on the effect of EHS is 3 and on the effect of IoB is 2 from CCAS. Consequently, the level of criticality (LC) of this asset scores 1, which means that the asset's criticality is Medium. From the FCAS, however, by taking account the difference in opinion among TPES when assessing this asset, the EHS score statistically is 2.5 (instead of 3), which is based on that 3 of the 8 TPES gave a score of 3, other 3 of 8 gave a score of 2 and the rest 2 of 8 were neutral (2.5 was used here to represent the neutral). For IoB, 4hrs, which represented the 'shutdown the production for 4 hours and equivalent loss of £25000', is used as IoB input. Consequently the level of criticality (LC) of the asset is 1.2, which can be interpreted using the fuzzy set definition as 80% Medium and 20% High (see Figure-7), and largely the asset's criticality is Medium same as that obtained from CCAS.

4.2. ADVANTAGES OF THE FUZZY SYSTEM (FCAS) OVER THE CRISP SYSTEM (CCAS)

Results of the cases study show that there are several advantages of the new fuzzy system over the current crisp system.

First, the fuzzy system can do what the conventional system offer, i.e. if crisp values from the third case discussed previously are inputted into the FCAS, then LC =1 is resulted, which is identical with the result obtained from CCAS. In addition, as shown in Table 10, both systems derive same results as far as the LC category is concerned, i.e. the assets 1 and 2 are in the category of High, the assets 3 and 4 are in the category of Medium and the assets 5 and 6 are in the category of Low.

Secondly the fuzzy system offers the possibility of much detailed criticality classifications than the conventional crisp system, by taking account of fuzziness and greyness existed in the real world production system and subjective/bias/imperfection of experts. It is known that the company also wants to rank assets within same level of criticality group in terms of importance to the production operation, which was one of the reasons that the third input, AMC was included in the CCAS. In FCAS this can be realised naturally by using EHS and IoB, to not only assess individual asset to different level of criticality but also to rank the assets within same criticality group. As shown in Table-10, FCAS system ranks all 6 assets based on their fuzzy scores, i.e. the asset 1 is the first and successively to the asset 6 as the last, in terms of criticality. However, the conventional CCAS can't provide the information, e.g. the asset 1 equals to the asset 2 in the High category, the asset 3 equals to the asset 4 in the Medium category and the asset 5 equals to the asset 6 in the Low category.

Thirdly, the fuzzy criticality system allows the team of the experts (TPES) to express their difference in opinion when assessing and scoring for each asset and takes those fuzziness and vagueness into the criticality assessment process. Consequently, the fuzzy system provides the criticality ranking in terms of the company's assets, with less bias and higher reliability.

The analysis of the all results obtained from the FCAS shows that some assets got fuzzy scores, either higher or lower than they should be according to experts' evaluation. This observation indicates that possibly there is room for fine tuning some of the 25 rules, which will be discussed in detail in another paper.

5. CONCLUSIONS

In modern Chemical plants, it is essential to establish an effective maintenance strategy, which will deliver financially driven results at optimized condition i.e. minimum cost and time by means of a criticality review of equipment in terms of maintenance. The crisp criticality assessment system (CCAS) of a local company's equipments is a very useful tool for the company's effective production maintenance management. However it is found that the system lacks flexibility and reliability and can be improved by introducing Fuzzy Set into the system. Consequently a new fuzzy criticality assessment system FCAS is developed and presented in this paper. The system is developed using Matlab fuzzy logic toolbox with a Mamdani inference method. It is found that:

1. This fuzzy system improved the existing crisp criticality assessment system; it can do what the conventional system can offer.
2. This fuzzy system offers the possibility of much detailed criticality classifications than the conventional crisp system, by taking account of fuzziness and greyness existed in the real world production system and bias/imperfection of experts. In addition to assess individual asset to deferent level of criticality (LC), FCAS can naturally use the input information of EHS and IoB to rank the assets within each LC group.
3. The fuzzy criticality system allows the team of the experts (TPES) to express their difference in opinion when assessing and scoring for each asset and takes those fuzziness and vagueness into the criticality assessment process. Consequently, the fuzzy system provides the criticality ranking in terms of the company's assets, with less bias and higher reliability.
4. Using the new FCAS, the quality of the company maintenance management can be further optimized by evaluation of the existing 25 rules and fine tuning some of them wherever necessary, which will be studied in future.

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