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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 equipment in maintenance. In this paper a fuzzy logic based criticality assessment system (FCAS) for the management of a local company's equipment maintenance is introduced. This fuzzy system is shown to improve the conventional crisp criticality assessment system (CCAS). Results from case studies show that not only can the fuzzy logic based system do what the conventional crisp system does but also it can output more criticality classifications with an improved reliability and a greater number of different ratings that account for fuzziness and individual voice of the decision makers.

KEYWORDS

Equipment criticality assessment, Maintenance management, Fuzzy system, Group decision making

1. INTRODUCTION

In modern chemical plants, it is essential to establish effective maintenance strategies. Criticality-based maintenance (CBM) is a prioritized approach to the maintenance of process equipment in the chemical process industries (CPI). In a process and hazard criticality ranking study (PHCR), each equipment item is evaluated with a 'what if it fails' scenario. This requires personnel with a thorough knowledge of the process/equipment under review. 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 1998). A decision making support system 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 a knowledge-based or expert system. More often, the two terms, expert systems (ES) and knowledge-based system (KBS) are used synonymously (Fasanghari and Montazer 2010).

In this paper a crisp criticality assessment system (CCAS), currently used in a local chemical company based in West-Yorkshire UK (Jani 2004), is presented; and the ambiguity and limitations of the system are identified. To improve the system robustness, fuzzy logic is applied to the CCAS system and a fuzzy criticality assessment system (FCAS) is developed. The advantages of the new FCAS system over the existing CCAS system are illustrated using some real life case studies.

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

2.1. CRITICALITY ASSESSMENT REVIEW

Criticality assessment review of equipment 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 *et al.* 1998, Lee and Hong 2003). Normally a Multi-Criterion Classification of the Critical Equipment (MCCCE), as defined by Felix *et al.* (2006), is used in a criticality review and assessment. Through the criticality review and assessment, companies can achieve:

- 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;
- 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.

Afey (2010) reported that through implementation of the equipment criticality assessment for the plant components, 22.17% of the annual spare parts cost are saved as a result of the preventive maintenance.

It's worthwhile to mention that in maintenance management, risk management and reliability engineering there are different types of criticality assessment at different levels with differing aim/objectives, as pointed out by Felix *et al.* (2006). Accordingly different methods have been formulated for identifying the critical equipment of a process, some are centred exclusively on the effect of failure on the service and others are based on the involved risk (Casal *et al.* 1999) or safety (Hokstand *et al.* 1995 and Cepin 2002). Braglia (2000) and Stamatis (2003) reported using the FMEA (Failure Mode and Effects Analysis) methods to determine and prioritise maintenance activity, rather than to classify the equipment itself.

2.2. CRITICALITY ASSESSMENT SYSTEM USED AT A LOCAL CHEMICAL COMPANY

Criticality assessment review of equipment at a local chemical company, in West-Yorkshire UK, was carried out during 2003-2004 (Jani 2004). The review looked at all the plant equipment in considerable detail, down to instrument level. The assessment process 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, which was the first step of the review and is detailed in this paper; and concurrently building and collecting data for consecutive tasks, such as critical spares analysis and Failure Mode and Effect Analysis (FMEA). The assessment method involved looking at the primary function of an item and establishing the consequences of loss of its function with three criteria/measures, i.e. 1) Environment, Health and Safety (EHS); 2) Impact on Business (IoB); and 3) Annual Maintenance Cost (AMC). The corporate 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).

Figure 1 –Flow chart map of criticality assessment procedure

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 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.

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

As the first step of the company's criticality assessment review (as shown in Figure 1), CCAS consists of three input scores and two output scores, as illustrated in Figure 2. Input One is the effect on 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 1. Input Two is the effect on 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 2. Input Three is the effect on 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 3.

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 4) 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:

$$TCS = EHS \times 4 + IoB \times 3 + AMC \times 1 \quad (1)$$

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 greater 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 become influential, and the weight factor should be considered differently (and consequently the third input may not be ignored as far as LC is concerned). The company used TCS score, 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 LC, this paper only considers the first two inputs.

Table 1- HAZARD impact

Table 2- BUSINESS impact

Table 3- MAINTENANCE impact

Table 4- Rule table for Level of Criticality (LC) score

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 2004). The Criticality Assessments were recorded in an Excel spread sheet, allowing easy manipulation and sorting of data. This spread sheet 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 CCAS at the case company include:

- Reducing the risk of serious failures by applying preventive maintenance strategy (such as FMEA) on the high LC group of assets, e.g. predictive/monitoring on-line;
- Reduced costs by reduced labour requirement (as low LC assets require less attention);
- Reduced usage of parts through unnecessary maintenance;
- Reduced planned maintenance stoppages attributed to unnecessary maintenance;
- High productivity due to 'critical assets' improved reliability.

Using 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, 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 based on 1524 items assessed (Jani 2004)

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

1, The input The input scores for EHS and IoB are simple, but have some drawbacks. For instance, when the TPES evaluate an individual asset, it is more likely that they may have different views on what scores for EHS (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 had 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. This issue is further discussed in section 4.

2, The output The output score on the level of criticality is an integral 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, 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 4 set up by the 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.

2.3. FUZZY EXPERT SYSTEM

The quality of decisions, in terms of repair priorities and resource assignment, is a critical factor for a production company. A decision support system plays a vital role in the decision process enhancement. Multi-Criteria Decision Making (MCDM) methods have received much attention from researchers and practitioners in evaluating, assessing and ranking alternatives across diverse industries (Behzadian *et al.* 2012). 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 Zadeh (1973). 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 presents 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 (Zimmermann 1992, Zadeh 1996). For example, a range of Fuzzy Set methods/systems have been adopted in the field of production/manufacturing planning/managements, such as a fuzzy decision support system (Coma *et al.* 2004), a fuzzy integrated multi-criteria group decision-making approach (Ertay 2011) and an extended fuzzy parametric programming-based approach (Safaei and Tavakkoli-Moghaddam 2009). Fuzzy logic also has been

used in ‘Criticality Assessment’. In Guo’s work (2009), an algorithm combining fuzzy comprehensive evaluation with a three-layer BP neural network was proposed in equipment criticality evaluation for a new petrochemical plant. Gargama (2011) and Braglia *et al.* (2003) used fuzzy logic in criticality assessment model for Failure Mode Effects and Criticality Analysis. Similarly, a system with an integration of fuzzy logic into a traditional Failure Mode and Effect Analysis (FFMEA) was reported in Despina’s work (2010) as a promising solution for a more accurate ranking of potential risks. Pillay and Wang (2003) proposed a new approach by using ‘fuzzy rule base’ and ‘grey relation theory’ to overcome some of the drawbacks of traditional FMEA approach. A literature survey conducted by Behzadian *et al.* (2012) showed the Fuzzy Technique for Order Preference by Similarity to Ideal Solution (FTOPSIS) as a very effective MCDM method, which works satisfactorily across different application areas, including Health, Safety and Environment Management.

Even though for different applications the corresponding structures of the fuzzy system/method may vary, the main tasks involved in developing a fuzzy logic decision system are similar: fuzzyfication, determining membership functions, setting fuzzy rules and defuzzyfication. Further discussion on different methods used in equipment criticality related analysis/assessment in comparison with the new FCAS is given in section 4.4.

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

3.1. FCAS SET-UP

The structure of the FCAS system is illustrated in Figure 4 (Alzaabi 2005). To keep the same system structure as CCAS, the new FCAS uses EHS and IoB as two fuzzy inputs. The fuzzy inference engine used is based on 25 IF-THEN rules with the Mamdani method and the system output, LC, is realised by de-fuzzyfication with Centroid method (Mamdani 1977).

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

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 5 for EHS and Table 6 for IoB. As antecedent 1, EHS has five labels, i.e. NH, SH, H, EH, DH. As antecedent 2, IoB 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.

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, a limited universe of discourse to the range of interest of application is used 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 crisp system (CCAS).

The membership function for IoB is established to give numerical meaning to each label as shown Figure 6. A trapezoidal membership function is used. IoB is assumed within a universe of discourse $U_2 = \{IoB / 0 \leq IoB \leq \infty\}$. Therefore, an unlimited universe of discourse to the range of interest of application is used 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 crisp system (CCAS).

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

Figure 5 –EHS membership functions

Figure 6 –IoB membership functions

Table 5- Fuzzy labels for EHS

Table 6- Fuzzy labels for IoB

3.1.2. The output: LC

Four fuzzy labels, i.e. L (Low), M (Medium), H (High) and VH (Very High), are assigned for LC, as shown in the right-hand column in Table 7. For comparison, the left-hand column of the table is the LC 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 $U_3 = \{LC / 0 \leq LC \leq 3\}$. A limited universe of discourse to the range of interest of application is used for LC. This also is identical with the set up of the crisp system (CCAS).

Table 7- Fuzzy labels for LC

Figure 7–Criticality classification membership functions

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 4 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 and Feyzioglu 2004). For 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 8. Since the five labels are defined for each input, the FAM is a 5×5 matrix.

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, e.g. ‘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 FACS in Table 8. The profile shows a transit of the level of criticality from 0 to 3 in representing Low, Medium, High and Very High respectively. The profile also indicates that EHS is superior to IoB in terms of effect on LC, same as in CCAS.

Table 8- Fuzzy Associative Memory (FAM) matrix for criticality classifications

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

3.1.4. De-fuzzyfication 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-fuzzyfication. ‘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-fuzzyfication. The final 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 7.

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 to key in the inputs (where 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; and simultaneously the input of IoB fires the rules of five, ten, fifteen, twenty, and twenty five respectively, as shown in the middle column. The result of the 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 7, the asset is classified as level 2 (or High) in terms of LC (as $1.5 < 1.93 < 2.5$), which is same as the result obtained from CCAS. Based on the definition of the membership functions for LC, 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 9.

Figure 9 –Inputs and output

4. DISCUSSIONS WITH CASE STUDY

4.1. SOME TREATMENTS IN THE FCAS DEVELOPMENT

4.1.1. Consideration of the individual voice of decision makers

How to facilitate the collaborative negotiation of group decisions is a technical issue in the multi-criteria decision-making system (MCDM) with a group of decision makers, as pointed out by Jing and Lu (2010). Boran *et al.* (2009) proposed an approach to aggregate the individual opinions of decision makers, which was adopted in this work. Let S_{ij}^k denote the scoring of the j th fuzzy input variable (either EHS or IoB) from k th member of the TPES for the i th equipment asset assessed. Assume that all individuals in the TPES, involved in the assessment process, carry equal weight, i.e. treating their opinions equally. The final score (representing group opinion), S_{ij} , on the j th input for the i th asset is then obtained by Formula 2:

$$S_{ij} = \frac{1}{l} \sum_{k=1}^l S_{ij}^k \quad (2)$$

l is the number of experts in the TPES, from 8 to 10 in this application.

The following example, which is mentioned in section 2.2.3, is used to illustrate how to use Formula 2. During the critical assessment of an agitator motor, which was used in the Effluent Plant to give motion to an agitator, the TPES had some differences in opinion on the EHS score for the agitator motor. Among the 10 members, 5 members gave a score of 0 and the other 5 members gave a score of 1. Based on the Formula 2, the group score for the agitator (asset i) in terms of EHS ($j = 1$):

$$S_{i1} = (0*5 + 1*5)/10 = 0.5$$

In CCAS, however, TPES had to agree on what score (with an integer value) should be assigned. Then, eventually, everybody agreed on $S_{i1} = 1$. 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.

As far as the IoB score is concerned, apart from no tolerance to the difference among TPES' opinions (the same as on EHS score mentioned previously), the CCAS treats, for example, a loss of £5000 and a loss of £50000 the same as they both score 2 (see Table 2). The FCAS, however, uses the actual estimated value as the input.

4.1.2. Choosing the shapes of fuzzy sets and membership functions

This is undoubtedly the most critical part of building a fuzzy system since the shape of the fuzzy set determines the correspondence between data and the underlying concept. Experimental evidence, however, points to a high tolerance for fuzzy shape approximation in most models/systems; that is, a fuzzy model will still behave well even when the fuzzy shapes are not precisely drawn. The conventional shape representations in engineering are either triangular or trapezoidal (Cox 1994). So a triangular membership function with 50% overlap is used for EHS and LC to adequately represent their linguistic and qualitative features with even region fuzzy sets. For IoB, by considering its quantitative feature (i.e. measured by hours/pounds) and its uneven fuzzy regions (e.g. 0 to 1 hour for LE and 8 to 24 hours for HE) a trapezoidal membership function is used. In addition, the general 'Sum-to-One' rule, defined in Formula 3 (Cox 1994) (stated as 'the sum of all points through the overlapping fuzzy sets should be equal to one'), is followed when setting a overlap among neighbouring fuzzy sets for fuzzy variable IoB as well as for EHS and LC.

$$\sum_{a=1}^n \mu_{ja}[x] = 1 \quad (3)$$

(where $\mu_{ja}[x]$ is the degree of membership of the a th fuzzy set for j th fuzzy variable with the value of x , and n is the number of fuzzy set regions for j th fuzzy variable, $n = 5$ for EHS and IoB, and $n = 4$ for LC.)

4.1.3. Fuzzy rules

24 of the 25 rules in the rule matrix in Table 8 for FCAS are identical with the rules designed by TPES used in the CCAS (see Table 4). One new rule, i.e. 'if EHS is DH and IoB is VE, then LC is VH', is introduced for the FCAS. This change helps to differentiate those assets with a high LC score at the high end of the ranking spectrum.

Table 9- Comparison of FCAS with CCAS

4.2. CASE STUDY

The power and robustness of the fuzzy criticality assessment system (FCAS) can be seen by looking and noting the differences between CCAS and FCAS, shown in Table 9, which includes critical assessments of 6 assets. Column 3 and Column 4 in Table 9 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 score base on Formula 2. Column 5 includes the outputs obtained from both CCAS and FCAS. Taking the case of asset No.3 in Table 9 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 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 is 2.5 (instead of 3), which is based on 3 of the 8 TPES giving a score of 3, 3 of 8 giving a score of 2 and the remaining 2 of 8 giving a neutral score (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 LC of the asset is 1.2, which can be interpreted using the fuzzy set definition for LC as 80% Medium and 20% High (see Figure 7), suggesting the asset's criticality is predominantly Medium (agreeing with the results from CCAS).

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

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

Firstly, the fuzzy system can do what the conventional systems 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 to the result obtained from CCAS. In addition, as shown in Table 9, both systems derive same results as far as the LC category is concerned, i.e. assets 1 and 2 are in the category of High, assets 3 and 4 are in the category of Medium and assets 5 and 6 are in the category of Low.

Secondly the fuzzy system offers much more detailed criticality classification than the crisp system, by taking account of the fuzziness and greyiness which exists in the real world production system and possible subjective/bias/imperfection of experts. It is known that the company wanted to rank assets within each level of criticality group, which was one of the reasons that the third criterion (AMC) was included in the CCAS. By just using EHS and IoB, FCAS can not only assess individual asset to different level of criticality but also rank the assets within the each criticality group. As shown in Table 9, FCAS system ranks all 6 assets based on their fuzzy scores, i.e. asset 1 is the most critical and asset 6 is the least critical. The conventional CCAS is unable to distinguish difference in criticality within each category, i.e. criticality of asset 1 is equal to 2 (High category), asset 3 is equal to 4 (Medium category), and asset 5 is equal to 6 (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 brings 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.

4.4. DISCUSSIONS

4.4.1. Comparison of FCAS with other fuzzy systems

As mentioned in section 2.3, different types of fuzzy system/methods are adopted by researchers and practitioners in evaluating, assessing and ranking alternatives across diverse industries, and FTOPSIS continues to work satisfactorily (Chakhar and Saad 2012, Boran *et al.* 2009). FFMEA was used by several researchers (Braglia *et al.* 2003, Despina and Avram 2010, Gargama 2011). The main differences of the method used in FCAS in comparison with those in literature, mainly FTOPSIS and FFMEA, have been identified as:

1, How expert voices are used In FCAS, experts (or decision makers) carry out the assessment tasks as a team, i.e. 8 to 10 experts with diverse backgrounds. Decisions are based on team meetings with discussion, debate and mutual influence. In the systems, such as FTOPSIS and FFMEA, experts carried out independent criticality assessments. They worked independently first in the assessment process (with no discussion and no mutual influence). Then, with different weighting assigned based on individual's level of expertise and using certain rules and mathematical algorithms, the final ranking was derived as an aggregation of the experts' independent opinions.

2, The numbers and the members of decision makers In FCAS, the number and the members of the TPES are flexible, i.e. it can be changed from time to time, from one plant site to another plant site if necessary. In contrast,

the numbers of experts, as well as the members of the experts involved, are prefixed as the main mathematics used in FTOPSIS (and FFMEA) is matrix, where predefined and prefixed size(s) for matrix (or string) is required.

3, The number of the equipment assets being assessed FCAS is designed and is suitable for large (or huge) numbers and differing number of items to be assessed or ranked. In the case company, more than ten thousand of the plant's equipment assets were assessed. The system also allows new equipment to be assessed and added into the system database at any required time.

4, The numbers of multi-criteria used In FCAS, fewer criteria are preferred, normally less than 4, as fewer criteria require an inference engine with less rules and/or simple formula, which also means less data/information required for experts to make decisions in the scoring/assessing process. In the system used in literature, a large numbers of criteria are normally used, which requires much detailed information/data for experts in the scoring/assessing process. The lack of adequate information is one of the main reasons causing difficulty of system implementation in industrial practice (Liu *et al.* 2010).

In summary, the main difference in comparison with other fuzzy logic systems (or methods/approaches) is that FCAS has an open structure in terms of the number of equipment assets to be assessed and the number/member of experts involved. And the TPES' 'voice', or a team voice, is used in the assessment process. FCAS is suitable for a large company's initial equipment criticality analysis (or the first step of a multi-steps equipment criticality review) in the company's Reliability Centered Maintenance (RCM) framework, where a large number of equipment assets are assessed at possible different plant sites with varied TPES member/numbers within a certain length of time period. The systems such as FTOPSIS and FFMEA, however, are more suitable for ranking and assessing handful highly important/critical equipment/systems assessed by a predefined group of experts or decision makers and supported with adequate data/information. The fuzzy criticality analysis of this kind is normally taken place as a subsequent step in a company's Reliability Centered Maintenance (RCM) framework.

4.4.2. Necessity in applications of fuzzy systems to real problem with real decision-makers

Criticality analysis has made some progress since its introduction into reliability studies in the 1960s, but clearly there are still areas that could benefit from more thought, discussion and research (Moss and Woodhouse 1999). The difficulty in the criticality analysis was the existence of uncertainty: imprecision, randomness and ambiguity. Fuzzy set theory (FST) has been proven as one of the most promising methods for reduction of these uncertainties. The main doubt concerning the actual applicability of FST to real industrial cases, as mentioned in Braglia's work (Braglia *et al.* 2003), is due to the difficulties arising during the fuzzy model design, i.e. in defining the (numerous) rules and membership functions required by this methodology. Furthermore, as pointed out by Liu *et al.* (2010), a significant amount of fuzzy set application in the literature is based on hypothetical information or test cases. Applications of fuzzy systems to real problem with real decision-makers are urgently needed to demonstrate the efficacy of the fuzzy systems approach for solving real-world problems. Our work is attempting to do so, i.e. the effectiveness of using fuzzy systems approach in an industrial practice is demonstrated through step-to-step comparison with a conventional approach and detailed fuzzy system setup (in terms of fuzzy rules and membership functions).

4.5. FUTURE WORK

It is known that fuzzy logic is not a single method suitable for the entire spectrum of problems encountered in uncertainty analyses. For addressing uncertainty, a hybrid approach was proposed in Guyonnet's work (Guyonnet *et al.* 2003), which combined Monte Carlo random sampling of probability distribution functions with fuzzy calculus. Also, because the hybrid approach takes advantage of the 'rich' information provided by probability distributions, while retaining the conservative character of fuzzy calculus, it is believed to hold value in terms of a 'reasonable' application of the precautionary principle. Liu *et al.* (2004, 2008) reported another hybrid approach, which combines fuzzy rule-based system with D-S theory for safety estimation and synthesis. Guo *et al.* (2009) studied an algorithm combining fuzzy comprehensive evaluation with a three-layer BP neural network for equipment criticality evaluation in Reliability Centered Maintenance (RCM).

To further improve the FCAS, the widely used FTOPSIS approach will be used in the equipment criticality ranking for those equipment cases in table 9. By comparison of the results from FTOPSIS and FCAS, issues related to enhancement of equipment criticality assessments can be identified and addressed. In addition the necessity of using a hybrid approach, as mention above, will be explored.

The analysis of the all results obtained from the FCAS shows that some assets received 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, and this will be discussed in the authors' other paper. Furthermore, other artificial intelligent methods, such as Artificial Neural Network (ANN) and/or Genetic Algorithms (GA) will be also considered in adaptive training and fine-tuning of the fuzzy system's setting parameters/variables, such as rules, weight factors, fuzzy set boundaries and fuzzy membership functions, which will improve the system's robustness and reliability. It is necessary to mention that any future research in this field should be both forward-looking and practically oriented.

5. CONCLUSIONS

The crisp criticality assessment system (CCAS) is a very useful tool for the case company's effective production maintenance management. However, it is found that the system's flexibility and reliability can be improved by introducing Fuzzy Sets into the system. Consequently a new fuzzy criticality assessment system (FCAS) 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.
2. This fuzzy system offers the possibility of much more detailed criticality classifications than the conventional crisp system, by taking into account of the fuzziness and greyness that exists in the real world production system and the possible bias/imperfection of experts. In addition to assessing individual asset to different LC, FCAS can also 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 opinions when assessing and scoring for each asset and brings those fuzziness and vagueness into the criticality assessment process. Consequently, the fuzzy system provides the criticality ranking of the company's assets with the possibility of less bias and higher reliability.
4. The main difference in comparison with other fuzzy logic systems (or methods/approaches), such as FTOPSIS and FFMEA, is that FCAS has an open structure in terms of the number of equipment assets to be assessed and the number of experts involved. Furthermore, in FCAS, the criticality assessment and analysis is based on expert-team 'voice' rather than expert-individual voice. Consequently, FCAS is suitable for a large company's initial equipment criticality analysis (or the first step of a multi-steps equipment criticality review) in the company's Reliability Centered Maintenance (RCM) framework.
5. As further work, the widely used FTOPSIS approach will be used in the equipment criticality ranking. Through comparison of the results from FTOPSIS and FCAS, issues related to enhancement of equipment criticality assessments will be identified and addressed. Other AI techniques and algorithms will be attempted for adaptive training and fine-tuning of the fuzzy system's settings.

A significant amount of fuzzy set application in the literature is based on hypothetical information or test cases. Applications of fuzzy systems to real problems with real decision-makers are urgently needed to demonstrate the efficacy of the fuzzy systems approach for solving real-world problems. Any future research in this field should be both forward-looking and practically oriented.

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Figure 9 –Inputs and output

Table 1- 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 2004)		

Table 2- 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 for 1-8 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 3- 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 4- 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)

Table 5- 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 6- 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 for 1-8 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

Table 7- Fuzzy labels for LC

Crisp Score	Fuzzy Score	Level of Criticality	Fuzzy Labels
0	≤ 0.5	Low	L
1	$0.5 < \leq 1.5$	Medium	M
2	$1.5 < \leq 2.5$	High	H
3	$2.5 <$	Very High	VH

Table 8- 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)

Table 9- 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)