**Dilbagh PANCHAL, PhD** E-mail: panchaldilbagh@gmail.com Department of Mechanical Engineering, Amity University, INDIA Prasenjit CHATTERJEE, PhD E-mail: prasenjit2007@gmail.com Department of Mechanical Engineering, MCKV Institute of Engineering, Howrah-711204, INDIA Rajendra Kumar SHUKLA, PhD **Department of Mechanical Engineering, Amity University, INDIA** Tanupriya CHOUDHURY, PhD E-mail: Tchoudhury@amity.edu **Department of Computer Science, Amity University, INDIA** Jolanta TAMOSAITIENE, PhD E-mail: jolanta.tamosaitiene@vgtu.lt **Civil Engineering Faculty, Research Institute of Smart Building Technologies** Vilnius Gediminas Technical University, LITHUANIA

# INTEGRATED FUZZY AHP-CODAS FRAMEWORK FOR MAINTENANCE DECISION IN UREA FERTILIZER INDUSTRY

Abstract: This paper proposes a novel integrated MCDM (multi-criteria decision-making) framework based on fuzzy AHP (Analytical Hierarchy Process) and a new fuzzy CODAS (Combinative Distance Based Assessment) approaches for solving the maintenance decision problem in a process industry. Under fuzzy AHP, a hierarchy structure related to the decision problem has been developed and the weights for different criteria and sub-criteria were computed using Geometric Mean (GM) method. These weights are further included in fuzzy CODAS approach to obtain the final ranking of the considered alternative maintenance strategies. Sensitivity analysis has also been performed for investigating the stability and validation of the proposed framework. The proposed framework was employed for selecting an optimal maintenance strategy for an Ammonia Synthesis Unit (ASU) of a urea fertilizer industry located in North India.

*Keywords:* Urea fertilizer industry, maintenance strategy selection, Fuzzy AHP-CODAS, sensitivity analysis.

JEL Classification: CO2, C44, C61, C63, L6

## 1. INTRODUCTION

From last few years ammonia emissions in urea fertilizer industries, and the reduction of these emissions, have become an increasingly challenging issue. The continuous ammonia emissions causes burning of skin, eyes, mouth, and lungs of human beings and therefore, accidental emissions resulting from sudden failure of plant operation comes into spotlight. The sudden failure of a plant operation due to inefficient maintenance policy not only affects the profitability of the considered industry but also has significant impact on human health. In a process industry, the maintenance manager faces enormous pressure to keep the systems in operating state as even a minor failure in the plant operation may results in serious accidents which directly contribute to the total production cost (Waeyenbergh and Pintelon, 2002). Existing literature confirms that maintenance cost for heavy process industries lies well over 15percent of the total production cost and minimization of this percentage may help in improving profitability(Wang et al., 2007; Ilangkumaran and Kumanan, 2009). In the past, due to minor failure of a sub-system/equipment of a plant one can observe serious damage to the society i.e. Union carbide plant leakage, Bhopal 1984, oil pipeline leakage, Nigeria1998, nuclear explosion, Chernobyl nuclear disaster, 1986 and oil tank farm fire, Jaipur 2009 etc. (Panchal and Kumar, 2016). Since, the sudden failure of a system may pollutes the environment heavily through toxic emissions therefore for clean and sustainable production of a plant, planning and implementation of suitable maintenance policy for a system is must.

#### **2. LITERATURE SURVEY**

In this section, a brief review of available literature related to maintenance decision-making for various real operating systems or subsystems of different process industries are provided. To name a few, Bevilacqua and Braglia (2000) applied analytic hierarchy process (AHP) method to formulate an optimal decision on maintenance policy for a real system in an Italian oil refinery. Bertolini and Bevilacqua (2006) have demonstrated the application of a goal programming approach for determining the optimum maintenance strategy for centrifugal pumps in an oil refinery industry. Pourjavad et al. (2013) have proposed analytic network process (ANP)-based technique for order of preference by similarity to ideal solution (TOPSIS) model for selecting the best maintenance policy in mining industry. Verbert et al. (2017) introduced a time based concept for making decision on condition based maintenance of multi component system of railway industry. The decision-making framework so implemented by various researchers in the above mentioned studies does not consider the uncertainties and vagueness involved in expert's judgments, and thus, the results of the analysis obtained using this vague information may have an element of uncertainty or inaccuracy. Therefore, accurate decision-making related to best maintenance

strategy for the system becomes quite difficult for the decision maker (DM). To overcome such limitations possessed by uncertain or vague data and subsequent uncertainty in the results, fuzzy methodology has been employed which eliminates uncertainties and imprecision involved in an expert's judgment, and hence, it has been considered as an effective tool for accurate decision making by various researchers. Al-Najjar and Alsyouf (2003) implemented fuzzy multiple-criteria decision-making (FMCDM) and fuzzy inference approaches to select the most efficient maintenance approach for the manufacturing plant. Sharma et al. (2005) presented the application of fuzzy inference theory for prioritizing the considered maintenance strategies in a paper plant. Wang et al. (2007) presented the fuzzy AHP approach application for searching the best maintenance decision for boiler unit in a thermal power industry located in China. Ghosh and Roy (2009) presented the use of a fuzzy decision making framework to select the optimal mix of maintenance for various components of the considered process plant. Ilangkumaran and Kumanan (2009) expounded the application of combined fuzzy decision making approaches to decide upon the best maintenance strategy for spinning mill. Fouladgar et al. (2012) proposed a FMCDM method based on complex proportional assessment (COPRAS) and AHP to assess the feasible maintenance strategy. Fuzzy AHP was utilized to calculate the weights of the evaluation criteria, while COPRAS method was applied to find the rankings of alternatives. Ilangkumaran and Kumanan (2012) applied the combined fuzzy Vise Kriterijumska Optimizacija Kompromisno Resenje (VIKOR) - fuzzy AHP approaches for making decision about best maintenance policy in textile industry. Tang et al. (2015) have proposed a fuzzy framework for equipments of oil and gas units. Jamshidi et al. (2015) presented a fuzzy risk-based maintenance framework for medical devices. Panchal and Kumar (2017) have expounded the application of fuzzy AHP and fuzzy TOPSIS approaches for selecting the best maintenance strategy for power generating unit of a thermal power plant. From the above reviewed literature, it is obvious that the projected integrated fuzzy MCDM framework has not yet been applied by any researcher for handling a decision making problem in any field. Considering this as a research gap the proposed fuzzy AHP and fuzzy COmbinative Distance-based ASsessment (CODAS) approaches-based integrated framework has been applied for deciding upon the optimal maintenance strategy of Ammonia Synthesis Unit (ASU) in a urea fertilizer industry located in north India.

#### **3. PROPOSED INTEGRATED FRAMEWORK**

The proposed integrated framework for optimal maintenance decision making of the considered industrial system has following two segments (See Figure 1).



Figure 1. Proposed integrated framework

In the first segment, under fuzzy AHP approach, various criteria and sub- criteria are identified through various sources such as literature review and expert's opinion. Using considered criteria, sub-criteria and alternatives, a decision hierarchy structure has been developed and using the expert's feedback and pair wise comparison matrices were generated. Using Geometric Mean (GM) method, weights of criteria and sub-criteria were tabulated. In the second segment, using global weights (criteria weight × sub-criteria weight) in fuzzy CODAS approach fuzzy negative solution values were

computed. Weighted Euclidean( $ED_i$ ) and weighted Hamming( $HD_i$ ) distances from the fuzzy negative solution( $\widetilde{ns}_i$ ) values were computed and are used further for tabulating the assessment scores( $\widetilde{AS}_i$ ) for each alternative. Ranking of alternatives was done in descending order. For measuring the stability and validity of ranking results sensitivity analysis has been performed.

# 4. Methods 4.1 FUZZY AHP

AHP is a type of additive weighting method developed primarily by Saaty, (1980). Fuzzy AHP is a highly effective tool that considers uncertainty in human judgment. Literature shows that triangular membership function (TMF) or trapezoidal membership function (TRMF) has been used by various researchers for considering the uncertainty and vagueness in experts' judgments. This study uses TMF due to its popularity and ease in computation. TMF converts qualitative information given by experts into TFN. The main steps of fuzzy AHP approach are presented as follows:

**Step 1:** Develop a hierarchy structure of the complex decision making problem in which goal is placed at highest level, alternatives are placed at a lower level and the criteria and their sub- criteria are placed between goal and alternatives.

**Step 2:** Generate pair wise comparison matrices for each level using crisp information collected from the experts in a well defined fuzzy linguistic scale as shown in Table 1.

Uncertain judgment	Fuzzy scale
Approximately important	1/2,1,2
Approximately X time more important <sup>a</sup>	(X-1,X,X+1)
Approximately X time less important	(1/X+1,1/X,1/X-1)
Between Y and Z time more important $^{\rm b}$	(Y, Y+Z/2,Z)
Between Y and Z time less important	(1/Z,2/Y+Z,1/y)
( <sup>a</sup> X=2,3,9),( <sup>b</sup> Y, Z=1,2,	9, Y <z)< td=""></z)<>

 Table 1: Fuzzy linguistic judgment scale (Wang et al., 2007)

To consider the uncertainty and imprecision in experts judgment we have used Triangular Membership Function (TMF) in this study. TMF has been used because of its popularity in ease and high accuracy in considering the vagueness of the raw data.

Step 3 For determining the weights of criteria and sub criteria we have used GM method for computing the relative normalized weights for different criteria and sub-

criteria. GM method was used because of its simplicity, easy determination of the maximum Eigen value and reduction in the inconsistency of judgments. The various steps involved in the GM method (Rao, 2007) are as discussed below:

Conversion of fuzzy comparison matrix into crisp comparison matrix: Using Eq.(1) fuzzy comparison matrices generated on the basis of expert's feedback are converted into crisp comparison matrix.

$$P(\check{A}) = \frac{P+4Q+R}{6} \tag{1}$$

• *Computation of Geometric Mean*: The GM of the*i*<sup>th</sup> row of the fuzzy comparison matrix is computed by using Eq.(2).

$$GM_{j} = \left[\prod_{i=1}^{n} a_{ij}\right]^{1/n}$$
(2)

Computation of normalized weight values: The normalized weight values of the *i*<sup>th</sup>row of crisp comparison matrix is given by Eq.(3).
 W<sub>j</sub> = GM<sub>j</sub>/∑<sup>n</sup><sub>j=1</sub> GM<sub>j</sub> (3)

**Step 4:** For controlling the results of AHP method, the consistency ratio (*CR*) for each pair wise comparison matrix is computed, and the value should be smaller than 0.1 for a matrix to be considered as consistent. Further, if a crisp comparison matrix is consistent, it means that its fuzzy pair wise comparison matrix is also consistent (Patil and Kant, 2014). The consistency index (*CI*) and consistency ratio (*CR*)of a comparison matrix is defined by the following Eqs. (Patil and Kant, 2014):

$$CI = \frac{\lambda_{max} - n}{n-1} \tag{4}$$

$$CR = \frac{CI}{RI} \tag{5}$$

Where,  $\lambda_{max} \rightarrow$  largest Eigen value;  $n \rightarrow$  size of the matrix

Here, the value of *RI* depends upon the order of matrix as shown in Table 2.

Size (n)	1	2	3	4	5	6	7	8
RI	0	0	0.52	0.89	1.11	1.25	1.35	1.40

Table 2: Random consistency index (RI) (Patil and Kant, 2014)

**Step 5:** The weights so computed are used to determine global weights (weights of criteria  $\times$  weights of sub-criteria).

In the present study, fuzzy AHP approach is used in comparison to other MCDM method because under fuzzy AHP only a few pair-wise comparison matrices are needed to be developed, which further makes this method simpler and systematic in terms of its application (Bai and Sarkis, 2010a).

## 4.3 FUZZY CODAS

CODAS is a new and influential MCDM tool which has been recently developed by Keshavarz Ghorabaee et al.(2016, 2017). Under this method, alternatives desirability is based on  $l^1$ -normand  $l^2$  -norm indifference spaces for criteria. The desirability of alternatives is based on combined Euclidean and Taxicab distances values from the negative ideal solution. Since, for searching the desirability of alternatives for a problem under fuzzy environment Euclidean and Taxicab distances values can't be used (as defined only for crisp environment) therefore fuzzy weighted Euclidean distance( $ED_i$ ) and fuzzy weighted Hamming distance( $HD_i$ ) (Li, 2007) are used for alternatives selection.Let there are m possible alternatives,ncriteriaand kdecision makers. The main steps involved in fuzzy CODAS approach are as follows:

**Step 1**: Generate fuzzy decision matrix  $(\tilde{X}_l)$  for each decision matrix and construct an average fuzzy decision matrix  $(\tilde{X})$  as represented by Eqs.(6) and (7) respectively.

$$\tilde{X} = \begin{bmatrix} \tilde{x}_{ij} \end{bmatrix}_{n \times m} = \begin{bmatrix} \tilde{x}_{n1l} & \tilde{x}_{n2l} & \cdots & \cdots & \tilde{x}_{nml} \end{bmatrix}$$
$$\tilde{X} = \begin{bmatrix} \tilde{x}_{ij} \end{bmatrix}_{n \times m} = \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \cdots & \cdots & \tilde{x}_{1m} \\ \tilde{x}_{21} & \tilde{x}_{22} & \cdots & \cdots & \tilde{x}_{2m} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ \tilde{x}_{n1} & \tilde{x}_{n2} & \cdots & \cdots & \tilde{x}_{nm} \end{bmatrix}; \quad i = 1, 2 \dots n; \ j = 1, 2 \dots m$$
(7)

 $\tilde{x}_{ij} = \sum_{l=1}^{k} \tilde{x}_{ijl}$ (8) Where,  $\tilde{x}_{ijl} \to$  fuzzy performance value of  $i^{th}$  alternative w.r.t  $j^{th}$  criterion and  $l^{th}$ 

decision maker;  $\tilde{x}_{ij} \rightarrow$  average performance value of  $i^{th}$  alternative w.r.t  $j^{th}$  criterion

Step 2: Generate a fuzzy normalized matrix  $(\tilde{R})$  by using the following Eqn.

$$\widetilde{\mathbf{R}} = \left[\widetilde{\mathbf{r}}_{ij}\right]_{n \times m} \tag{9}$$
Where,

$$\tilde{\mathbf{r}}_{ij} = \begin{cases} \tilde{x}_{ij} / \prod_{i}^{max} \xi(\tilde{x}_{ij}); forbenifitcriteria\\ 1 - (\tilde{x}_{ij} / \prod_{i}^{max} \xi(\tilde{x}_{ij})); forcostcrieteria\\ \tilde{\mathbf{r}}_{ij} \rightarrow \text{Normalized fuzzy values} \end{cases}$$
(10)

**Step 3:**Compute fuzzy weighted normalized matrix by using the Eqn. as follows  $\tilde{V} = [\tilde{v}_{ij}]_{n \times m}$ ; i = 1, 2, ..., n; j = 1, 2, ..., m (11)

Where  $\tilde{v}_{ij} = \tilde{r}_{ij} * w_j$  (12)

 $\tilde{v}_{ij} \rightarrow$  is a TFN represented by  $(\tilde{P}_{ij}, \tilde{Q}_{ij}, \tilde{R}_{ij})$ 

 $w_j \rightarrow$  Weights of criteria computed under fuzzy AHP approach whose values lies between [0,1]

Step 4: Tabulate fuzzy negative solution values by using the relation as

$$\widetilde{NS} = \left[\widetilde{ns}_j\right]_{1 \times m} \tag{13}$$

$$\widetilde{ns}_{i} = {\min_{i} \widetilde{v}_{ij}}$$
(14)

**Step 5:** Compute  $ED_i$  and  $HD_i$  distances for each alternative from fuzzy negative solution value by using the Eqs. as follows

$$ED_i = \sum_{j=1}^m E_d(\tilde{v}_{ij}, \tilde{n}\tilde{s}_j); \tag{15}$$

$$HD_i = \sum_{j=1}^m H_d(\tilde{v}_{ij}, \tilde{ns}_j).$$
<sup>(16)</sup>

Step 6: Establish relative assessment matrix using the following Eqs:

$$RA = [p_{ik}]_{n \times n} \tag{17}$$

Where,

$$p_{ik} = (ED_i - ED_k) + (t(ED_i - ED_k) \times (HD_i - HD_k)); k = 1,2,3 \dots \dots n$$
(18)

 $t \rightarrow$  Threshold function

Also, Threshold function is represented as:

$$t(x) = \begin{cases} 1 & if |x| \ge \emptyset \\ 1 & if |x| < \emptyset \end{cases}$$
(19)

 $\emptyset \rightarrow$  Threshold parameter of the function and its value is to be set by the decision maker in the range of 0.01 - 0.05

Step 7: Compute the assessment score for each alternative by using the Eqn:

$$AS_i = \sum_{k=1}^n \mathbf{p}_{ik} \tag{20}$$

Step 8: On the basis of assessment score we can rank the alternative in decreasing order.

In comparison to other MCDM approaches, fuzzy CODAS is introduced within fuzzy AHP because of its ability to consider relative importance among the distances for making decision on alternative priority.

# **5. ILLUSTRATIVE EXAMPLE**

To exemplify the application of the proposed framework, ASU system of a urea fertilizer industry has been considered in the present study.ASU, one of the critical functional units of the considered industry consists of various subsystems/equipment namely compressor, hot and cold heat exchanger, reactors, ammonia converter, pump, pipes, safety valve, pressure gauge etc. Currently, due to high inimitability in the market and ease in implementation, Corrective Maintenance (CM) strategy is in use for the considered system. With this maintenance strategy, the current plant operation report indicates towards the sudden rise of the number of breakdowns. Therefore, a good maintenance strategy that improves system availability and reduces operation cost is warranted. Under this situation, for maintenance manager, selection of best mix of maintenance strategy is more preferable rather than to employ a separate maintenance policy for each subsystem/equipment of the considered system. Hence, for the selection of best mix of maintenance strategy for ASU, the proposed fuzzy AHP-fuzzy CODAS approaches based integrated framework has been implemented in the present study and is discussed as follows:

#### 5.1 Application of proposed framework

#### **5.1.1**Application of fuzzy AHP

Under fuzzy AHP approach, on the basis of intensive discussions with maintenance experts' team (comprising one maintenance manager and three senior maintenance personnel) and exploring available literature related to maintenance policy selection (; Wang et al., 2007; Bevilacqua and Braglia, 2000; Ramadhan et al., 1999; Ilangkumaran and Kumanan, 2009), six important criteria and their seventeen sub-criteria have been identified. Five maintenance strategies (Table 3)were considered as alternatives. Using these criteria, sub-criteria and alternatives a hierarchy structure (Figure 2) related to the problem has been developed. In the current study, the generated hierarchy structure has been considered as approved one since it was developed under the directions of maintenance expert's team. Further, comparison matrices were generated for each level. On the basis of feedback from maintenance experts, crisp information related to each criterion and sub-criteria have been collected. The collected crisp information has been translated into TFN using a well-defined fuzzy linguistic Wang scale (Table 1). Using these TFN, fuzzy comparison matrices were prepared for each level. The fuzzy comparison matrices are generated for criteria and sub-criteria with respect to goal (selection of optimal maintenance strategy) and criteria ( $G_1$  and  $G_2$ ) respectively. Tables 4-6 show some sample comparison matrices. Once the comparison matrices have been generated, weights were computed for each criterion and their sub-criteria by using GM method (Rao, 2007). Using Eq. (1), the

fuzzy comparison matrix for criteria (Table 4) has been converted into crisp comparison matrix as shown in Table 7.Using Eqs. (12) and (13) the values of CI and CR have been computed as 0.0698 and 0.0562. Since CR value for the criteria matrix is less than 0.1 it means that the matrix so generated on the basis of expert's feedback is consistent and is acceptable for further analysis. Similarly, the weight calculations were done for the sub-criteria and their consistencies have been checked. Further, global weights (Weights of criteria ×Weights of sub-criteria) were calculated as shown in Table 8.

Sl. no	Maintenance strategy	References
1	Corrective Maintenance (CM)	(Ilangkumaran and Kumanan, 2009)
2	Predictive Maintenance (PDM)	(Wang et al., 2007)
3	Condition Based Maintenance (CBM)	(Wang etal., 2007; Ilangkumaran and Kumanan, 2009)
4	Reliability Centered Maintenance (RCM)	(Ilangkumaran and Kumanan, 2012)
5	Preventive Maintenance (PM)	(Wang et al., 2007)

Table 3: Alternatives for the considered system

Goal	G <sub>1</sub>	G <sub>2</sub>	G <sub>3</sub>		G <sub>5</sub>	G <sub>6</sub>
G1	(1,1,1)	(1/5,1/4,1/3)	(1/4,1/3,1/2)	•••••	(2,3,4)	(1,2,3)
G <sub>2</sub>	(3,4,5)	(1,1,1)	(1,2,3)	•••••	(4,5,6)	(5,6,7)
G3	(2,3,4)	(1/3,1/2,1)	(1,1,1)	•••••	(3,4,5)	(4,5,6)
G4	(1,2,3)	(1/4,1/3,1/2)	(1/3,1/2,1)	•••••	(5,6,7)	(3,4,5)
G5	(1/4,1/3,1/2)	(1/6,1/5,1/4)	(1/5,1/4,1/3)	•••••	(1,1,1)	(2,3,4)
G <sub>6</sub>	(1/3,1/2,1)	(1/7,1/6,1/5)	(1/6,1/5,1/4)		(1/4,1/3,1/2)	(1,1,1)

Table 4: The fuzzy comparison matrix for criteria w.r.t to goal

CR value for the defuzzified version of this matrix is  $0.0562 \le 0.1$ 



Figure 2. Fuzzy AHP Hierarchy structure

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G1	C11	C <sub>12</sub>	C <sub>13</sub>
C11	(1,1,1)	(3,4,5)	(2,3,4)
C <sub>12</sub>	(1/5,1/4,1/3)	(1,1,1)	(1/3,1/2,1)
C <sub>13</sub>	(1/4,1/3,1/2)	(1,2,3)	(1,1,1)

CR value for the defuzzified version of this matrix is  $0.0156 \le 0.1$ 

$G_2$	C <sub>21</sub>	C <sub>22</sub>	C <sub>23</sub>
C <sub>21</sub>	(1,1,1)	(4,5,6)	(3,4,5)
C <sub>22</sub>	(1/6,1/5,1/4)	(1,1,1)	(1,2,3)
C <sub>23</sub>	(1/5,1/4,1/3)	(1/3, 1/2, 1)	(1,1,1)

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Table 6: The fuzzy comparison matrix for the sub- criteria w.r.t criteria G<sub>2</sub>

CR value for the defuzzified version of this matrix is  $0.0807 \le 0.1$ Table 7: Crisp comparison matrix for criteria

Criteria	G <sub>1</sub>	G <sub>2</sub>	G3	G4	G5	G <sub>6</sub>
G <sub>1</sub>	1	1/4	1/3	1/2	3	2
$G_2$	4	1	2	3	5	6
G3	3	1/2	1	2	4	5
G4	2	1/3	1/2	1	6	4
<b>G</b> 5	1/3	1/5	1/4	1/6	1	3
G <sub>6</sub>	1/2	1/6	1/5	1/4	1/3	1

CR value for the crisp comparison matrix of criteria is  $0.0562 \le 0.1$ Table 8: Weight of criteria, sub criteria and global weight

Sub-criteria	Criteria	Sub-criteria	Global weight
Hardware cost $(C_{11})$		0.6250	0.0623
Software cost ( $C_{12}$ )	0.0007	0.1365	0.0136
Staff training cost ( $C_{13}$ )	0.0997	0.2385	0.0238
Human safety $(C_{21})$		0.6869	0.2581
Environmental safety (C <sub>22</sub> )	0.3758	0.1864	0.0700
Facilities (C <sub>23</sub> )		0.1265	0.0475
Production loss $(C_{31})$		0.4699	0.1167
Spare part inventories (C <sub>32</sub> )	0 2484	0.1195	0.0297
Fault identification (C <sub>33</sub> )	0.2464	0.4105	0.1020
Pipe leakage risk (C <sub>41</sub> )		0.6490	0.1152
Compressor failure risk	0 1775	0.1210	0.0215
Safety valve failure risk	0.1775	0.2290	0.0406
Insulation quality $(C_{51})$		0.7681	0.0434
Design quality $(C_{52})$	0.0565	0.2318	0.0131
Pipe joint quality ( $C_{53}$ )	0.0303	0.2025	0.0114
Implementation Difficulty		0.2000	0.0084
Labor acceptance (C <sub>62</sub> )	0.0419	0.8000	0.0335

# 5.1.2 Application of fuzzy CODAS in alternative ranking

Under fuzzy CODAS approach, on the basis of crisp information (converted into TFN using Table 1) collected from three experts, three fuzzy judgment matrices were generated. Due to space limitations, only one such matrix (prepared on the basis of feedback of expert-1) is shown in Table 9.

Maintenance strategy	C11	C <sub>12</sub>		C <sub>61</sub>	C <sub>62</sub>
СМ	(2,3,4)	(1,2,3)	•••••	(1,2,3)	(0.5,1,2)
PDM	(2,2.5,3)	(3,4,5)	•••••	(1, 1.5, 2)	(0.33,0.4,0.5)
CBM	(0.5, 1, 2)	(2,3,4)	•••••	(0.33,1/2,1)	(0.33, 0.5, 1)
RCM	(3,4,5)	(0.5, 1, 2)	•••••	(0.5, 1, 2)	(2,3,4)
PM	(0.33,0.5,1)	(0.25, 0.33, 0.5)	•••••	(0.5, 1, 2)	(0.33,0.4,0.5)

Table 9: Fuzzy evaluation matrix for alternatives on the basis of Expert-1 feedback

Using these three fuzzy evaluation matrices, an aggregate fuzzy decision matrix has been generated (Table 10) for considering the wide ranges of expert's feedback. **Table 10: Aggregate fuzzy decision matrix for alternatives** 

Maintenance strategy	C <sub>11</sub>	C <sub>12</sub>		C <sub>61</sub>	C <sub>62</sub>
СМ	(2.3,3,4.5)	(1.6,2.6,3.9)	•••••	(1.4,2,3)	(0.8,1,2.6)
PDM	(2,2.8,3)	(3.2,4,5.3)	•••••	(1,1.5,2.4)	(0.38,0.4,0.6)
CBM	(0.8, 1, 2.2)	(2.5,3.2,4.8)	•••••	(0.36,1/2,1.2)	(0.33,0.5,1.5)
RCM	(4,5.5,6.7)	(0.7, 1, 2.1)	•••••	(0.52, 1, 2.3)	(2.4,3.1,4.6)
PM	(0.38, 0.5, 1.2)	(0.35,0.34,0.9)	•••••	(0.53, 1, 2.1)	(0.37,0.4,0.6)

Further, to bring the raw data of aggregate fuzzy decision matrix into a comparable scale, a normalized fuzzy decision matrix (Table 11) has been generated by normalizing the aggregate fuzzy decision matrix.

Table 11: Normalized fuzzy decision matrix for alternatives

Maintenance strategy	C <sub>11</sub>	C <sub>12</sub>		C <sub>62</sub>
CM	(.08,.13,.17)	(0.1,.15,.24)	••••	(0.15,0.38,0.48)
PDM	(0.13,0.14,0.19)	(.07,0.10,0.12)	•••••	(0.63,0.95,1.0)
CBM	(.15,.33,.41)	(.07,.10,.13)	•••••	(0.22, .66, 1.0)
RCM	(.04,.05,.07)	(.13,.28,.40)	•••••	(0.06,0.09,0.12)
PM	(.28,.66,.87)	(.22,.97,.94)	•••••	(0.55,0.83,0.89)

The global weights (Table 8) obtained under fuzzy AHP approach were multiplied with normalized fuzzy decision matrix for obtaining the weighted fuzzy decision matrix as shown in Table 12.

Maintenance strategy	C <sub>11</sub>	•••••	C <sub>62</sub>
СМ	(0.0053,0.0079,0.0103)	•••••	(0.0049,0.0127,0.0159)
PDM	(0.0079,0.0085,0.0118)	•••••	(0.0212,0.0318,0.0335)
CBM	(0.0093,0.0206,0.0257)	•••••	(0.0074,0.0221,0.0335)
RCM	(0.0026,0.0032,0.0044)	•••••	(0.0020,0.0030,0.0039)
PM	(0.0171,0.0411,0.0541)	•••••	(0.0184,0.0276,0.0299)

Table 12: Weighted fuzzy decision matrix for alternatives

Afterwards, fuzzy negative solutions values were computed by using Eqs.(13) and (14). Using fuzzy weighed normalized matrix $ED_i$  and  $HD_i$  distances of each alternative has been computed by using Eqs.(15) and (16). The fuzzy negative solution and distance values are shown in Table 13. Using Table 13 and Eqs. (17-19), relative assessment matrix (*RA*) has been tabulated. In the present study the value of  $\emptyset$  is considered as 0.02. Using the values of RA matrix and Eqn. (20), assessment values for each alternative was computed and the alternatives were ranked according to decreasing values of assessment score as shown in Table 14.

#### 6. Results discussion and sensitivity analysis

From Table 14, it has been noted that for strategy PM, the assessment score  $(\widetilde{AS}_i)$  value is 1.3754 which is higher than other maintenance strategies. Therefore, it is regarded as the best maintenance strategy for the considered system. On the basis of  $\widetilde{AS}_i$  values, the final order of preference of the considered alternatives is found to be PM > CBM > PDM > RCM > CM.

For testing the stability and validity of the proposed framework, sensitivity analysis has been performed. Threshold values have been varied in the range of 0.01-0.05 and the assessment score  $(\widetilde{AS}_i)$  values were noted for each fixed value. From the noted $\widetilde{AS}_i$  values, same ranking results were obtained for each threshold value which confirms the stability and validity of the raking results. The sensitivity analysis based ranking results obtained at different  $\emptyset$  values are represented in Figure 3. This figure clearly shows the stability of ranking results as obtained by the proposed integrated framework.

Integrated Fuzzy	AHP-Codas	Framework for	Maintenance	Decision in	n Urea	Fertilizer
Industry						

Criteria	СМ	PDM	PM	$\widetilde{NS}_j$
C11	(0.021,0.032,0.042)	•••••	(0.070,0.170,0.223)	(0.010,0.013,0.018)
C <sub>12</sub>	(0.002,0.003,0.006)	•••••	(0.009, 0.024, 0.024)	(0.001,0.0026,0.003)
C <sub>13</sub>	(0.004,0.014,0.019)	•••••	(0.004, 0.009, 0.009)	(0.002,0.0032,0.004)
C <sub>21</sub>	(0.009,0.012,0.011)	•••••	(0.007,0.009,0.011)	(0.007,0.0098,0.011)
$C_{22}$	(0.0039,0.0062,0.009)	•••••	(0.002,0.003,0.004)	(0.002,0.0037,0.004)
C <sub>23</sub>	(0.0024,0.0034,0.004)	•••••	(0.003,0.008,0.011)	(0.002,0.003,0.004)
C <sub>31</sub>	(0.001, 0.0020, 0.002)	•••••	(0.022,0.022,0.016)	(0.001, 0.001, 0.002)
C <sub>32</sub>	(0.001, 0.003, 0.005)	•••••	(0.001, 0.005, 0.009)	(0.001, 0.001, 0.001)
C <sub>33</sub>	(0.001,0.002,0.002)	•••••	(0.003, 0.007, 0.009)	(0.001,0.002,0.002)
$C_{41}$	(0.0023,0.003,0.004)	•••••	(0.006,0.019,0.029)	(0.0016,0.002,0.002)
$C_{42}$	(0.0055,0.009,0.014)	•••••	(0.006,0.013,0.034)	(0.004, 0.006, 0.007)
C <sub>43</sub>	(0.0021,0.003,0.005)	•••••	(0.002,0.006,0.006)	(0.0008, 0.001, 0.002)
C <sub>51</sub>	(0.003,0.005,0.006)	•••••	(0.003, 0.006, 0.008)	(0.003,0.005,0.006)
C <sub>52</sub>	(0.003, 0.0062, 0.007)	•••••	(0.005,0.013,0.022)	(0.002, 0.003, 0.005)
C <sub>53</sub>	(0.0001,0.0001,0.0002)	•••••	(0.0001,0.001,0.0001)	(0.0004,0.0001,0.0001)
C <sub>61</sub>	(0.017,0.026,0.037)	•••••	(0.021,0.045,0.086)	(0.016,0.038,0.074)
C <sub>62</sub>	(0.021,0.056,0.070)	•••••	(0.081,0.122,0.132)	(0.009,0.013,0.017)
$ED_i$	0.089	0.212	0.325	
HD <sub>i</sub>	0.296	0.627	1.034	

Table 13: Fuzzy Normalized matrix with fuzzy negative solution and distances value

#### 7. Research limitations and managerial implication

The selection of an optimal maintenance strategy for ASU of a urea fertilizer industry depends upon qualitative and quantitative information provided by maintenance experts, which is subjective in nature. Therefore, the results obtained may have an element of inaccuracy and personal bias. The findings of our study would benefit practitioners in the following ways:

- Help maintenance managers to select optimal maintenance strategies for their plants thus reducing maintenance cost.
- Increase system sustainability by minimizing incidents of sudden failure.
- Better utilization of maintenance resources.

Maintenance ranking results have been provided to the maintenance experts of the considered unit. Once the management took decision to implement these results a detailed verification and validation of the proposed framework results may be evaluated accordingly.

Table 14: Relative assessment matrix with assessment score and alternative ranking							
Maintenance strategy	СМ	PDM	CBM	RCM	PM	$\widetilde{AS}_i$	Ranking
CM	0	0	0	-0.0087	0	-0.0087	5
PDM	0.2461	0	-0.0022	0.2286	0	0.4725	3
CBM	0.2505	0.0022	0	0.2330	0	0.4857	2
RCM	0.0087	0	0	0	0	0.0087	4
PM	0.4724	0.2263	0.2219	0.4549	0	1.3754	1

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# 8. Conclusions

With an increase in the complexities of real industrial systems, maintenance decision making has become a challenge for maintenance managers. In the present study, the authors have proposed a novel integrated MCDM framework for the selection of an optimal maintenance strategy for ASU of a urea fertilizer industry. The selected maintenance strategy would we useful in increasing system availability and reducing the maintenance budget of the considered unit. In order to overcome the uncertainty and vagueness in human judgment, the authors have incorporated fuzzy set

theory within proposed framework. Further, fuzzy AHP tool was used to compute global weights for various sub-criteria which were included in fuzzy CODAS approach for computing the assessment score  $(\widetilde{AS}_i)$  values. On the basis of  $\widetilde{AS}_i$  values, PM was found to be the best maintenance strategy for the considered unit. For examining the stability and validation of decision results, sensitivity analysis was conducted and the sensitivity results confirmed the stability of the proposed framework.

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