Occupational Injuries Predictions – Fuzzy AHP modeling

Dr. S. Joseph Robin

Associate Professor, Department of Mathematics, Scott Christian College (Autonomous) Nagercoil – 629 003, Kanyakumari District, Tamil Nadu, India. sjosephrobin@yahoo.com

Abstract-In this paper the use of the expert system in solving predictive models for occupational injuries in the Brick-work firms. Fuzzy synthetic analysis is used in the analysis and triangular Fuzzy with AHP is used to derive weights for different risk factors. The analysis is able to provide linguistic risk levels and quantified risks in assessing the overall risk.

Keywords–Expert system, Extent Analysis, Clustering, task factors.

I. INTRODUCTION

"An expert system is a computer program that solves problems that heretofore required significant human expertise by using explicitely represented domain knowledge and computational decision procedures". In this work an attempt is made to use the expert system to solve predictive models for occupational injuries in the Brick-work units in an around the Kanyakumari District, Tamilnadu, India, using the Fuzzy AHP models. Here the tools developed in Fuzzy-set theory (FST) is used to assess the variability in the human abilities and their performance. FST is a rule-based expert system to predict the possibility of an occupational injury in the forearm and on hand. This will address the cumulative trauma disorders (CTD's) since fuzzy is an exceptional way to manage qualitative assessments and thus the humaninference process in providing user-friendly inference through the use of natural language. Only because of the ability of FST to offer a natural-language inference and a graded degree of injury rating it is used in the methodology development here.

II. METHODOLOGY

A pre tested Questionnaire was administered with 100 randomly selected female participants (it is to be noted that carrying of the bricks are only done of Females in the study area due to the lower level of payment) and the needed informations viz: the type of injury, duration and the risk are assessed.

The details assessed are

- 1. risk factors
- 2. risk levels
- 3. membership function for each

4. hazard curve for risk with each linguistic variable.

After the assessment of the risk with respect to each factor the relative contribution of each factor with respect to the overall injury are assessed.

Now the use of AHP in model building has to be done. To do this we need the details of the following:

A. 1) Fuzzy sets

If X is a collection of objects denoted generically by x, then a fuzzy set \widetilde{A} in X is $\widetilde{A} = \{x, \frac{\mu}{A}(x) \mid x \in X| \}, \overline{\mu}(x)$ is called the membership function or grade of membership of x in \widetilde{A} that maps X to the membership space M. The range of the membership function is a subset of the nonnegative real numbers whose supremum is finite. Elements with a zero degree of membership are not listed.

2) Support

The support of a fuzzy set \widetilde{A} , $S(\widetilde{A})$, is the crisp set of all $x \in X$ such that $\frac{\mu}{\widetilde{A}}(x) > 0$.

3) α -cuts

The set of elements that belong to the fuzzy set \widetilde{A} at least to the degree α is called the α -level set.

$$A_{\alpha} = \{ x \in X \mid \overset{\mu}{\underline{A}}(x) \geq \alpha \}$$

 $A'_{\alpha} = \{x \in X \mid \overset{\mu}{A}(x) > \alpha\}$ is called "strong α level set" or "strong α -cut"

4) Convexity

A fuzzy set à is convex if

$$\begin{array}{l} \underset{\widetilde{A}}{\overset{\mu}{}}(\lambda x_{1}+ \ \overline{1-\lambda} \ x_{2}) \geq \min \ \{ \underset{\widetilde{A}}{\overset{\mu}{}}(x_{1}), \ \underset{\widetilde{A}}{\overset{\mu}{}}(x_{2}) \}, \\ x_{1}, x_{2} \in X, \lambda \in [0,1] \end{array}$$

alternatively, a fuzzy set is convex if all α -level sets are convex.

5) Cardinality

For a finite set \widetilde{A} , the cardinality $|\widetilde{A}| = \sum_{x \in X} \prod_{\widetilde{A}}^{\mu} (x)$ is defined as

 $\|\widetilde{A}\| = \frac{|\widetilde{A}|}{|x|}$ is called the relative cardinality of \widetilde{A}

B. Analytic Hierarchy process (AHP)

The AHP incorporates Judgements and personal values in a logical way. It depends on

imagination, experience and knowledge to structure the hierarchy of a problem and on logic, intution and experience to provide Judgements. It provides a single easily understood, flexible model for a wide range of unstructured problem.

In the case of the multicriteria decision making the main problem is prioritization of criteria. Determining weights for priorities. There are several methods viz: eigen vector method, weighted least squares method and linear programming. In this we need the fuzzy analytic hierarchy process (FAHP) by Chang (1992) and (1996).

The first step is to use triangular fuzzy numbers for pairwise comparison by using FAHP scale and the second step is to use the extent analysis for priority weights. In Table I below we give the linguistic variables and their triangular fuzzy value.

LINGUISTIC VARIABLE THEIR TRIANGULAR FUZZY VALVES (TFV) (ℓ , M, U)						
Sl. No.	Linguistic scale for Importance	Fuzzy numbers	Membership function	Domain	Triangular fuzzy values	
1	Equally important	ĩ	$_{\rm M}^{\mu}({\rm x}) = (3-{\rm x}) / (3-1)$	$1 \le x \le 3$	(1,1,1) (1,1,3)	
2	Weakly important	ĩ	${}^{\mu}_{M}(x) = (x-1) / (3-1)$ ${}^{\mu}_{M}(x) = (5-x) / (5-3)$	$\begin{array}{c} 1 \leq x \leq 3 \\ 3 \leq x \leq 5 \end{array}$	(1,3,5)	
3	Essential or strongly important	ĩ	${}^{\mu}_{M}(x) = (x-3) / (5-3)$ ${}^{\mu}_{M}(x) = (7-x) / (7-5)$	$\begin{array}{c} 3 \leq x \leq 5 \\ 5 \leq x \leq 7 \end{array}$	(3,5,7)	
4	Very Strongly important	7	${}^{\mu}_{M}(x) = (x-5) / (7-5)$ ${}^{\mu}_{M}(x) = (9-x) / (9-7)$	$5 \le x \le 7$ $7 \le x \le 9$	(5,7,9)	
5	Extremely Preferred	9	$_{\rm M}^{\mu}({\rm x}) = ({\rm x-7}) / (9-7)$		(7,9,9)	

TABLE I

If factor i has one of the above numbers assigned to it when compared to factor j, then j has the reciprocal value when compared to i Reciprocal of the above is

 $\widetilde{\mathsf{M}}_{1}^{-1} = \left(\frac{1}{u_{1}}, \frac{1}{\mathsf{m}_{1}}, \frac{1}{l_{1}}\right)$

B. Chang's extent analysis

Let $X=\{x_1, x_2, ..., x_n\}$ be an object set and $U=\{u_1, u_2, ..., u_m\}$ be a goal set. According to chang each object is taken and analysis for each goal g_i , is performed, respectively. Hence there will be m extent analysis values viz:

 $M_{g_i}^1, M_{g_i}^2, \dots, M_{g_i}^m, i=1,2,...,n$

Here all the $M_{g_i}^j$ (j=1,2,m) are Triangular Fuzzy Numbers (TFN) (a, b,c). The steps in the extent analysis are:

Step 1:

The value of fuzzy synthetic extent with respect to ith object is defined as

 $\begin{array}{c} S_i = \sum_{j=1}^m \ M_{g_i}^j \otimes \sum_{i=1}^m \ \Sigma_{j=1}^m \ M_{g_i}^j \end{array} \right] \\ To obtain \qquad \sum_{j=1}^m \ M_{g_i}^j \ perform the fuzzy \end{array}$

addition operation of m extent analysis values for a particular matrix as

 $\sum_{j=1}^{m} M_{g_{i}}^{j} = \left(\sum_{j=1}^{m} a_{j}, \sum_{j=1}^{m} b_{j}, \sum_{j=1}^{m} c_{j} \right)$ and to obtain it's inverse perform the fuzzy

and to obtain it's inverse perform the fuzzy addition operation of $M_{g_i}^i(j=1,2..,m)$ values such that

 $\begin{array}{l} \underset{j=1}{\overset{\text{unat}}{\sum_{i=1}^{n} \sum_{j=1}^{m} M_{g_{i}}^{j} = \left(\sum_{i=1}^{n} a_{i}, \sum_{i=1}^{n} b_{i}, \sum_{i=1}^{n} c_{i} \right) \text{ and } \\ \text{the inverse is} \\ \left(\frac{1}{\sum_{i=1}^{n} c^{i}}, \frac{1}{\sum_{i=1}^{n} b^{i}}, \frac{1}{\sum_{i=1}^{n} a^{i}} \right) \end{array}$

Step II:

The degree of possibility of $M_2 = (a_2, b_2, c_2)$ $\geq M_1 = (a_1, b_1, c_1)$ is defined as

$$\begin{split} V(M_2 \geq M_1) &= Sup[\min \ \overset{\mu}{M_1}(x), \ \overset{\mu}{M_2}(x)] \\ \text{This can be equivalently expressed as:} \\ V(\widetilde{M}_2 \geq \widetilde{M}_1) &= h_{gt}(\widetilde{M}_1 \cap \widetilde{M}_2) \end{split}$$

$$= \begin{cases} 1 &, \text{ if } b_2 \ge b_1 \\ 0 &, \text{ if } a_1 \ge c_2 \\ \frac{a_1 - c_2}{(b_2 - c_2) - (b_1 - a_1)} &, \text{ otherwise} \end{cases}$$

In the Fig. 1, below d gives the ordinate of the highest intersection point D between ${}^{\mu}_{M_1}$ and ${}^{\mu}_{M_2}$



Fig. 1 The intersection between M_1 and M_2 to compare M_1 and M_2 , both the values of $V(M_1 \geq M_2)$ and $V(M_2 \geq M_1).$

Step III:

The degree of possibility for a convex fuzzy number to be greater than k convex fuzzy numbers $M_i(i=1,2,...k)$ is defined as

 $V(M \ge M_1, M_2, ..., M_k) = V[(M \ge M_1) \text{ and } (M \ge M_2)$ and ... $(M \ge M_k)]$

 $= \min V(M \ge M_i), (i=1,2,\ldots k)$ Assuming that $d^1(Ai) = \min V(Si \ge Sk)$ for $k = 1,2,\ldots,n; k \ne i.$

Then the weight vector is given by $W' = (d'(A1), d'(A2), ..., d'(An))^T$ where Ai=(i=1,2,...,n) are n elements.

Step IV:

By normalizing, the normalized weight vectors are $W=(d(A_1), \ldots, d(An))^T$, where W is a non-fuzzy number.

The AHP results for the three modules are presented in Table II to IV and comparison is in Table V.

 TABLE II

 AHP results: Task – related risk factors

Ranking	Factors	Relative Weight
1	Improper positioning of hand	0.315
2	Improper cutting of Bricks	0.206
3	Over addition of improper sized stands	0.196
4	Over loading	0.142
5	Over duration	0.141

TABLE III AHP RESULTS: PERSONAL-RISK FACTORS

Ranking	Factors	Relative Weights
1	Previous CTD	0.427
2	Diabetics	0.214
3	Thyroid problem	0.141
4	Age	0.094
5	Arthoritis	0.124

TABLE IV AHP RESULTS: ORGANIZATIONAL-RISK FACTORS

Ranking	Factors	Relative Weights
1	Distance	0.366
2	Exposure to sunlight	0.269
3	Sanitation	0.201
4	Rest period	0.085
5	Training	0.079

TABLE V AHP RESULTS: MODULE-RISK COMPARISON

Ranking	Module	Relative Weights
1	Task	0.642
2	Personal	0.255
3	Organizational	0.103

The results of FAHP presented in Table 2-5 indicate that the task factor is the most significant

followed by personal and the least with the organizational factors. The second has nearly 40% of the first and the last has only 16% of the first.

C. Clustering

The main object is to group similar (or parallel) objects into subgroups. It may be based on similarities, distances in the n-dimensional space etc. Here AHP is used to generate the weight for the relative impact of each risk factor. Interaction with the experts also were made to identify the conditions for the identification of natural clusters. All these results in to the identification of four factors viz:

1. arthritis and age,

2. age and diabetes

3. diabetes and obesity

4. obesity and thyroid problems

It is to be noted that in 1-4, a factor may exist in more than one cluster. This is the advantage of using fuzzy in clustering.

A modular methodology is used for the evaluation of risk factors. Three modular categories were identified.

They are : task-related, personal-related and occupational – related.

Now for each module:

- 1. Five risk factors were identified.
- 2. For each factor linguistic risk levels (LRL's) are identified.
- 3. Membership functions are created for each risk factor and
- 4. Hazard curve / membership functions for normalizing risk associated with a particular linguistic value of a variable are made.

After knowing the individual risk associated with each factor, the relative contribution of each in the overall injury level is also estimated.

The cluster analysis indicated two clusters for Task related factors:

Cluster 1 consisting of Improper positioning of hand, Improper cutting of Bricks and the over addition of improper sands.

Cluster 2 consisting of over loading and over duration.

Regarding the personal-risk factors there is only one cluster combining diabetes, arthritis and age. In the case of organizational factors no clustering occurred.

The personal and organizational – characters to get together produce notable synergetic effects such as Distance with diabetics, age with more exposure to sunlight and antogonistic effect of Arthurities with rest.

III. CONCLUSION

The analysis provides linguistic risk levels as well as quantified risks in assessing the overall risk of injury for the working class toiling in the Bricks production Industry in Kanyakumari District, Tamilnadu, India.

REFERENCES

- Armstrong T and Chaffin D (1979) Carpal tunnel synchrome and selected personal attributes; J. occupant. Med. Vol.21 no.7; 481-486.
- [2] Armstrong T and Lifshits Y (1988) Evaluation and Design of, Jobs for control of cumulative trauma dis-orders; unpublished Res.Rep.Univ. Miching an, ctr. Economics.
- [3] Burnette J (1989), CTD-123; a Cumulative trauma disorder risk assessment mode, unpublished Doctoral dissert; North Carolina State Univ., Dept, Industrial Engg. 1-60.
- [4] Smith M and Zehal D (1990); cumulative trauma injuries control effects in selected wisconsin manufacturing plants; Advances in Industrial Economics and Safety II; London: Taylor – Francis, 259-265.
- [5] Steward J (1991); "Safety Engineer", Seagate Technology, personal communication.