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TREND ANALYSIS OF TISSUE ZINC CONTENT FOR MEDICAL RADIATION WORKERS USING FUZZY LOGIC

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Abstract: Various radiation workers are occupationally exposed to chronic low dose ionizing radiations in addition to natural background radiations. But till date there is no such well-accepted biomarker to resolve actual effect (hazardous or beneficial) of chronic low dose radiation on human subjects, though many schools of thoughts are prevailing in this regard. Present study investi-

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gates the zinc status in the peripheral blood and scalp hair of medical radiographers in comparison to age and economy matched normal healthy individuals in fuzzy environment. To capture more information it is always necessary to integrate the experts knowledge, experience and perception with the experimental information. In view of this, according to medical experts, the overall decisions of zinc content for several period (2-34 years) of occupational radiation exposures are considered as fuzzy. Therefore, a fuzzy regression technique is suggested to capture the trend of tissue zinc content based on time of exposures in fuzzy environment.

AMS Subject Classification: 03B52, 78A40, 94D05
Key Words: chronic low dose X-radiation, radiographers, zinc, atomic absorption spectrometry (AAS), fuzzy logic, fuzzy regression model, least squares method

1. Introduction

Radiation workers are occupationally exposed to low dose ionizing radiations in a chronic way. As per radiation safety standard of Atomic Energy Regulatory Board of India, cumulative effective dose limit for each consecutive block of five years is 100 mSv (1 mSv = 0.1 cGy for X-ray) for individual radiation workers and annual effective dose in a calendar year should not exceed the limit of 30 mSv (Chatterjee et al [2]). On an average an Indian diagnostic medical radiation worker receives 1.46 mSv ionizing radiation (X-ray) per year occupationally in addition to natural background radiation. However, till date researchers differ regarding actual biological effects of chronic low dose radiations on human subjects. Paucity of radiobiological data in this regard is also evident in Kuzin [9], Chatterjee et al [2], Fabrikant [7], Sagan [12], Wolff [13] and Ikushima [8]. In fact, most of the low dose radiobiological predictions suffer from intrinsic uncertainty since these are generally based on linear extrapolation of data from high dose radiation effect studies (Kuzin [9], Sagan [12] and Wolff [13]). Further, the researchers of low dose radiobiological study mostly depend on physical dosimeters like thermoluminescence device (TLD) in radiobiological dosimetry. But, this physical approach is unable to calculate or assess the actual radiation exposure in an extensive mammalian system like human body. In recent times, researchers are trying to overcome this radiobiological dosimetric problem through identifying suitable biomarkers, which can simultaneously assess the radiation dose and its effect at the biosystem levels. Our group has already demonstrated the significant changes in the trace metal contents of different tissues of radiation workers and chronic low dose X-irradiated rats (Chatterjee et al [3], [4], [5] and Majumdar et al [10]). The present study has opted to assess the zinc status in blood and hair of medical radiation workers. The trace metal like zinc is not only vital in maintaining biological integrity of mammalian systems but also a potent indicator of the pathology of the system in its excess and its deficiency states in Chatterjee et al [2] and Paul et al [11]. In this context, it also may be noted that the biological data from the effect research are gaining attentions of the mathematicians. Besides nonlinearity they have noticed overlapping, ambiguity and inexactness in biological data (Chatterjee et al [5]). In view of this, fuzzy logic (Zadeh [16]) is recommended here as an appropriate tool. Here radiographers and normal healthy individuals of mixed age groups are investigated to capture the inherent trend of zinc content in their hair and blood over the period of radiation exposures. Practically, it is very difficult for the medical experts to assess the perfect amount of zinc rather some approximated value for certain age group. Rather the experts feel comfortable to express their opinion (Chakraborty [1]) in natural languages aiming at the experimental observations because the factors are really uncertain. In this way the subjectivity of the experts in terms of the cognitive factors like perception, experience, thinking etc gets involved in making a suitable decision in medical science. E.g. suppose an expert is asked to make a general comment on the zinc status for radiographer and normal healthy individuals of an approximate age group. Then s/he naturally answers like that "If the time of exposure is approximately 2.25 years then the zinc content in radiographer's (i) hair is around 150.3 mg/g and (ii) blood is approximately 10.3 mg/ml" depending upon the experimental observations. Here the predicates "approximately", "more or less" and "around" etc are fuzzy. Thus the two factors viz. zinc content and time of exposure become fuzzy. Now the paper develops a fuzzy regression model based on the fuzzy input and fuzzy output to find the trend of zinc for radiographer and normal individuals. Fuzzy regression analysis has become an important tool for prediction under fuzzy framework. Many researchers (Yang et al [15], [14]) have worked on it.

Section 2 demonstrates the medical study where Subsection 2.1 describes the materials and methods under study. And the procedure for the estimation of zinc with atomic absorption spectrometry (AAS) for normal and medical radiographers is studied in Subsection 2.2. Also Subsection 2.3 enhances the fuzzification process to transform the raw data into the reliable fuzzy data. In Section 3, a methodology for fitting nonlinear fuzzy regression model is devised for linguistic variables. Finally the model is fitted with the medical data for

Analyte	Wavelength (nm)	Current (mA)	C_2H_2 flow (lit/min)	Burner height (mm)
Zn	213.9	6	2.4	4

Table 1: Instrumental conditions for AAS

normal person and radiographers and results are discussed in Section 4.

2. Medical Study and Fuzzification

2.1. Materials and Methods

In this study, scalp hair and peripheral blood from 58 medical radiographers (27-60 years of age) those of who are occupationally exposed to X-radiation works for 2-34 years and economy matched normal healthy volunteers were collected for estimation of zinc with atomic absorption spectrometry (AAS). From each medical radiographer and healthy volunteer 2 ml of peripheral blood and 50-100 mg (about 4-5 cm long) distal ends of scalp hair were collected.

2.2. Estimation of Zinc with AAS

Zinc content in blood and hair samples was estimated with AAS (Model AA646 Shimadzu, Japan) using following procedure. Each blood sample was slowly wet digested with 15 ml H_2O_2 for 30 min, then 5 ml of conc. HNO_3 was added and slowly digested for 2 h. Finally 3 ml of 70% $HClO_4$ was added and strongly heated until it was converted into white dry mass. It was dissolved in water and volume was made upto 10 ml in a volumetric flask. Hair filaments were first washed in acetone (AR, Merck, Germany) and then with double distilled water. Next each sample was slowly wet digested in 20 ml of conc. HNO_3 and 1 ml of 70% $HClO_4$ was added. Then the solution was heated until it was converted into a white dry mass. It was dissolved in deionized and double distilled water and volume was made upto 10 ml in volumetric flask. In zinc estimation with AAS, 1 ppm working solution was prepared from 5000 ppm stock solution of $ZnCl_2$. Finally zinc was estimated with flame AAS against reagent blank by using standard procedures (Chatterjee et al [5], Majumdar et al [10]) with required instrumental conditions as follows

In hair and blood, zinc is estimated as mg/g and mg/ml respectively. For each age category, the content of zinc in blood and hair is observed for a particular time of exposure (TOE). The process is repeated a number of times with the reasonable variation of TOE and note the content of zinc corresponding to different TOE. In practice, the amount of zinc in blood and hair is varying quantity that can be estimated by transforming into fuzzy numbers. Therefore the TOE and zinc content are considered here as linguistic variables.

2.3. Fuzzification Process

Definition. (Fuzzy Number) A fuzzy number $\widetilde{A} = (m, \alpha, \beta)$ is a convex and normalized fuzzy set whose membership function is of the following form

$$\mu_{\widetilde{A}}(t) = \begin{cases} 1 - (\frac{m-t}{\alpha}), & \text{if} \quad m - \alpha \le t \le m, \\ 1 - (\frac{t-m}{\beta}), & \text{if} \quad m \le t \le m + \beta. \end{cases}$$

It is convinced that a fuzzy number is more informative than a crisp number though vagueness is inherent there. In view of this, a heuristic fuzzification process is devised here. If there is no outlier, it can be statistically said that the more concentration is at mean of all the observations for that specific age group. Spreads are computed in terms of range. Suppose we have p experimental observations $x_1, x_2, ..., x_p$ of TOE for certain age group. Therefore, a triangular fuzzy number $\widetilde{A} = (m, \alpha, \beta)$, where m = more concentration = $\frac{1}{p}\sum_{i=1}^{p} x_i; \alpha = m - \min(x_i)$ and $\beta = \max(x_i) - m$.

Then the linguistic variables TOE and zinc content consider the fuzzy numbers as experimental output. For the sake of simplicity, all the fuzzy numbers are assumed to be triangular in the form through out the paper.

3. Trend Analysis with Fuzzy Data

Predictive modeling for retrieving the inherent trend in the imprecise data has now become an important research issue. The regression analysis is popular statistical technique for modeling with precise data. In view of this, the fuzzy regression analysis (Yang et al [15], [14]) has been developed for imprecise data. In this paper, the aim is to fit a regression model with the fuzzy input and fuzzy output. It is observed that the present raw data set (see Appendix) fits well with the second-degree polynomial ignoring the fuzziness. So when the data truly converted into a fuzzy data through the fuzzification process, a second-degree fuzzy polynomial model, called here parabolic fuzzy regression model is required to fit for trend analysis. In practice, the dependent variable 'zinc content' and the independent variable 'time of exposure (TOE)' become linguistic by integrating with radiation biologists experience, perception and thinking etc. Therefore an attempt is made here in fitting a fuzzy parabolic model with these linguistic variables. Let us assume that the 'zinc content in hair' and 'time of exposure' are denoted by $\widetilde{Y}$ and $\widetilde{X}$ respectively. Therefore a fuzzy parabolic model for fuzzy input-output is as follows

$$\widetilde{Y} = \widetilde{a_0} + \widetilde{a_1} \otimes \widetilde{X} + \widetilde{a_2} \otimes \widetilde{X}^2 \,, \tag{1}$$

where the model parameters $\widetilde{a_j}$ are also fuzzy. $\otimes$ denotes the extended multiplication operator between two fuzzy numbers. The observed data $\{(\widetilde{y}, \widetilde{x})\}$ collected on $\{(\widetilde{Y}, \widetilde{X})\}$ are transformed into triangular fuzzy numbers. Here the linguistic variables and fuzzy parameters are expressed as triangular fuzzy numbers, i.e., $\widetilde{y} = (m_y, \alpha_y, \beta_y)$, $\widetilde{x} = (m_x, \alpha_x, \beta_x)$ and $\widetilde{a_j} = (m_{a_j}, \alpha_{a_j}, \beta_{a_j})$. Multiplication of any two fuzzy numbers approximates another fuzzy number according to Dubois and Prade [5]. Therefore the R.H.S of model (1) can be re-written as follows

$$\begin{aligned}\widetilde{Y} = \widetilde{a_0} + \widetilde{a_1} \otimes \widetilde{X} + \widetilde{a_2} \otimes \widetilde{X}^2 &= (m_{a_0}, \alpha_{a_0}, \beta_{a_0}) + (m_{a_1}, \alpha_{a_1}, \beta_{a_1}) \otimes (m_x, \alpha_x, \beta_x) \\ &+ (m_{a_2}, \alpha_{a_2}, \beta_{a_2}) \otimes (m_x, \alpha_x, \beta_x) \otimes (m_x, \alpha_x, \beta_x) \cong (m, \alpha, \beta) \,, \end{aligned} \tag{2}$$

where $m = m_{a_0} + m_{a_1} m_x + m_{a_2} m_x^2; \alpha = \alpha_{a_0} + m_{a_1}\alpha_x + m_x \alpha_{a_1} + 2m_{a_2}\alpha_x m_x + \alpha_{a_2} m_x^2$ and $\beta = \beta_{a_0} + m_{a_1}\beta_x + m_x\beta_{a_1} + 2m_{a_2}\beta_x m_x + \beta_{a_2} m_x^2$.

The fuzzy regression parameters are estimated by least squares method based on the n observations $\{(\widetilde{y_i}, \widetilde{x_i})\}_{i=1,2,..,n}$. In particular, the relationship between the actual and approximated fuzzy data point is

$$\widetilde{y_i} = (m_i, \alpha_i, \beta_i) i.e., (m_{y_i}, \alpha_{y_i}, \beta_{y_i}) = (m_i, \alpha_i, \beta_i) \,, \quad \forall i = 1, 2, .., n \,. \tag{3}$$

Therefore the Euclidean distance between $(m_{y_i}, \alpha_{y_i}, \beta_{y_i})$ and (m_i, α_i, β_i) that leads to form the objective function for estimation of the parameters. Assume that $\hat{\widetilde{a}}_0 = (\hat{\widetilde{m}}_{a_0}, \hat{\widetilde{\alpha}}_{a_0}, \hat{\widetilde{\beta}}_{a_0}), \hat{\widetilde{a}}_1 = (\hat{\widetilde{m}}_{a_1}, \hat{\widetilde{\alpha}}_{a_1}, \hat{\widetilde{\beta}}_{a_1})$ and $\hat{\widetilde{a}}_2 = (\hat{\widetilde{m}}_{a_2}, \hat{\widetilde{\alpha}}_{a_2}, \hat{\widetilde{\beta}}_{a_2})$ are estimated by minimizing the objective function. Then

$$J = J_1 + J_2 + J_3 \,, \tag{4}$$

where

$$J_1(m_{a_0}, m_{a_1}, m_{a_2}) = \sum_{i=1} (m_i - m_{y_i})^2 \,,$$

$$J_2(\alpha_{a_0}, \alpha_{a_1}, \alpha_{a_2}) = \sum_{i=1} [(m_i - \alpha_i) - (m_{y_i} - \alpha_{y_i})]^2 \,,$$

$$J_3(\beta_{a_0}, \beta_{a_1}, \alpha_{a_2}) = \sum_{i=1} [(m_i + \beta_i) - (m_{y_i} + \beta_{y_i})]^2 .$$

The normal equations are obtained by taking partial derivatives of equation (4) to 0 as

$$\begin{pmatrix} \hat{\tilde{m}}_{a_0} \\ \hat{\tilde{m}}_{a_1} \\ \hat{\tilde{m}}_{a_2} \end{pmatrix} = M^{-1} \times \begin{pmatrix} \sum_i m_{y_i} \\ \sum_i m_{y_i} m_{x_i} \\ \sum_i m_{y_i} {m_{x_i}}^2 \end{pmatrix},$$

where

$$M = \begin{pmatrix} n & \sum_i m_{x_i} & \sum_i {m_{x_i}}^2 \\ \sum_i m_{x_i} & \sum_i {m_{x_i}}^2 & \sum_i {m_{x_i}}^3 \\ \sum_i {m_{x_i}}^2 & \sum_i {m_{x_i}}^3 & \sum_i {m_{x_i}}^4 \end{pmatrix},$$

and

$$\begin{pmatrix} \hat{\tilde{\alpha}}_{a_0} \\ \hat{\tilde{\alpha}}_{a_1} \\ \hat{\tilde{\alpha}}_{a_2} \end{pmatrix} = M^{-1} \times$$

$$\begin{pmatrix} \sum_i \{\hat{m}_{a_0} + \hat{m}_{a_1} m_{x_i} + \hat{m}_{a_2} m_{x_i}^2 - \hat{m}_{a_1} \alpha_{x_i} - 2\hat{m}_{a_2} m_{x_i} \alpha_{x_i} - (m_{y_i} - \alpha_{y_i})\}^2 \\ \sum_i m_{x_i} \{\hat{m}_{a_0} + \hat{m}_{a_1} m_{x_i} + \hat{m}_{a_2} m_{x_i}^2 - \hat{m}_{a_1} \alpha_{x_i} - 2\hat{m}_{a_2} m_{x_i} \alpha_{x_i} - (m_{y_i} - \alpha_{y_i})\}^2 \\ \sum_i m_{x_i}^2 \{\hat{m}_{a_0} + \hat{m}_{a_1} m_{x_i} + \hat{m}_{a_2} m_{x_i}^2 - \hat{m}_{a_1} \alpha_{x_i} - 2\hat{m}_{a_2} m_{x_i} \alpha_{x_i} - (m_{y_i} - \alpha_{y_i})\}^2 \end{pmatrix},$$

$$\begin{pmatrix} \hat{\tilde{\beta}}_{a_0} \\ \hat{\tilde{\beta}}_{a_1} \\ \hat{\tilde{\beta}}_{a_2} \end{pmatrix} = M^{-1} \times$$

$$\begin{pmatrix} \sum_i \{(m_{y_i} + \beta_{y_i}) - \hat{m}_{a_0} - \hat{m}_{a_1} m_{x_i} - \hat{m}_{a_2} m_{x_i}^2 - \hat{m}_{a_1} \beta_{x_i} - 2\hat{m}_{a_2} m_{x_i} \beta_{x_i}\}^2 \\ \sum_i m_{x_i} \{(m_{y_i} + \beta_{y_i}) - \hat{m}_{a_0} - \hat{m}_{a_1} m_{x_i} - \hat{m}_{a_2} m_{x_i}^2 - \hat{m}_{a_1} \beta_{x_i} - 2\hat{m}_{a_2} m_{x_i} \beta_{x_i}\}^2 \\ \sum_i m_{x_i}^2 \{(m_{y_i} + \beta_{y_i}) - \hat{m}_{a_0} - \hat{m}_{a_1} m_{x_i} - \hat{m}_{a_2} m_{x_i}^2 - \hat{m}_{a_1} \beta_{x_i} - 2\hat{m}_{a_2} m_{x_i} \beta_{x_i}\}^2 \end{pmatrix}.$$

The above unconstrained minimization technique may lead to negative spreads. Yang et al [14] have been proposed the reformulation of fuzzy number when spreads are negative as follows:

(i) If $\alpha_a < 0$ and $\beta_a < 0$ then $\widetilde{a} = (m_a, -\beta_a, -\alpha_a)$.

ii) If $\alpha_a < 0$ and $\beta_a > 0$ then

$$\widetilde{a} = \begin{cases} (m_a, 0, \beta_a), & \text{if} \quad |\beta_a| > |\alpha_a|, \\ (m_a, 0, -\alpha_a), & \text{if} \quad |\beta_a| < |\alpha_a|. \end{cases}$$

Time of Exposure ($\widetilde{X}$)	Zinc content ($\widetilde{Y}_{NB}$)	Zinc content ($\widetilde{Y}_{RB}$)
(2.25, 0.25, 0.25)	(11.2, 1.8, 1.4)	(10.3, 0.9, 1)
(5, 0.5, 0.5)	(11.2, 1.01, 1.4)	(6.28, 0.98, 1.2)
(7.5, 0.5, 0.5)	(10.4, 1.3, 1.7)	(6.5, 1.3, 0.9)
(10, 1, 0.5)	(10.7, 1.6, 1.9)	(6.1, 0.8, 0.9)
(15, 1, 1)	(11, 1.2, 1.2)	(6.27, 0.97, 1.2)
(20, 1, 1)	(11.3, 1.4, 1.2)	(6.2, 2, 1)
(24, 1, 1)	(10.7, 1.5, 1.8)	(4.9, 0.8, 1)
(30, 2,2.5)	(8.2, 1.8, 1.3)	(5.24, 1, 1.2)

Table 2: Fuzzification of the raw medical data for blood

(iii) If $\alpha_a > 0$ and $\beta_a < 0$ then

$$\widetilde{a} = \begin{cases} (m_a, \alpha_a, 0), & \text{if} \quad |\alpha_a| > |\beta_a|, \\ (m_a, -\beta_a, 0), & \text{if} \quad |\alpha_a| < |\beta_a|. \end{cases} \tag{5}$$

Therefore, the fitted parabolic fuzzy regression medel is written as follows:

$$\hat{\widetilde{Y}} = \hat{\widetilde{a}}_0 + \hat{\widetilde{a}}_1 \otimes \widetilde{X} + \hat{\widetilde{a}}_2 \otimes \widetilde{X}^2 . \tag{6}$$

4. Results

The data has been generated by repeating the experiment a number of times for each of the age groups. Since initially it is difficult to consider a crisp value that never include expert's experience, knowledge and perception. In view of this, the fuzzification process has been applied to cover all the data repeated for each age group. Fuzzy logic is capable of integrating experience, perception and feelings about the status of radiographer's zinc in hair and blood respectively. Using the fuzzification process, the raw data has been transformed into fuzzy numbers as:

Case (i): Zinc Content in Radiographer's Blood. Now the transformed data on time of exposure ($\widetilde{X}$) and zinc content ($\widetilde{Y}$) for normal persons ($\widetilde{Y}_{NB}$) and radiographers ($\widetilde{Y}_{RB}$) are represented in Table 2.

Therefore the estimated fuzzy parameters for normal persons and radiographers are computed and given in Table 3. Since some of the spreads are negative, the parameters are reformulated using Yang and Ko's method. Now the parameters are $\hat{\widetilde{a}}_0$= (10.34, 1.67, 1.52), $\hat{\widetilde{a}}_1$= (0.16, 0.01, 0.072) and $\hat{\widetilde{a}}_2$=

Normal person	Radiographer
$\hat{m}_{a_0} = 10.34$; $\hat{\alpha}_{a_0} = 1.67$; $\hat{\beta}_{a_0} = 1.52$	$\hat{m}_{a_0} = 9.49$; $\hat{\alpha}_{a_0} = -0.78$; $\hat{\beta}_{a_0} = 1.113$
$\hat{m}_{a_1} = 0.16$; $\hat{\alpha}_{a_1} = -0.072$; $\hat{\beta}_{a_1} = -0.01$	$\hat{m}_{a_1} = -3.75$; $\hat{\alpha}_{a_1} = 0.082$; $\hat{\beta}_{a_1} = 0.009$
$\hat{m}_{a_2} = -0.007$; $\hat{\alpha}_{a_2} = 0.003$; $\hat{\beta}_{a_2} = 0.0007$	$\hat{m}_{a_2} = 0.008$; $\hat{\alpha}_{a_2} = -0.003$; $\hat{\beta}_{a_2} = -0.0004$

Table 3: Estimated parameters by least squares method

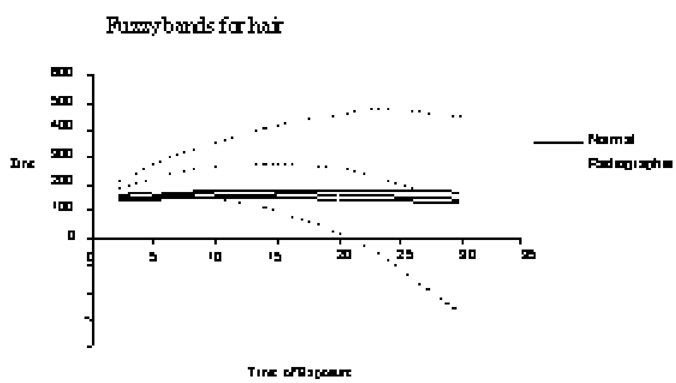

Figure 1:

Time of Exposure ($\widetilde{X}$)	Zinc content ($\widetilde{Y}_{NH}$)	Zinc content ($\widetilde{Y}_{RH}$)
(2.25, 0.25, 0.25)	(149.8, 8.5, 11.5)	(150.3,10, 13)
(5, 0.5, 0.5)	(160.9, 11.6, 5.39)	(239.8, 42, 40.7)
(7.5, 0.5, 0.5)	(160.1, 15.7, 5.77)	(276.1, 76.8, 50.1)
(10, 1, 0.5)	(165.5, 10.2, 7.63)	(245.3, 65.9, 95)
(15, 1, 1)	(162.8, 10.2, 7.71)	(256.5, 66, 46.1)
(20, 1, 1)	(166.9, 16.6, 14.4)	(216, 65, 44)
(24, 1, 1)	(150.5, 20.3, 10.4)	(247.5, 62.5, 41.5)
(30, 2,2.5)	(149.3, 12.9, 13)	(116.7, 17.5, 11.9)

Table 4: Fuzzification of the raw medical data for hair

(-0.007, 0.003, 0.0007) for normal person's blood. Hence the fitted model for normal person is as follows

$$\widetilde{y}_{NB} = (10.34, 1.67, 1.52) + (0.16, 0.01, 0.072) \otimes \widetilde{x} + (-0.007, 0.003, 0.0007) \otimes \widetilde{x}^2 . \quad (7)$$

In the same way, Hence the fitted model for radiographer's blood is

$$\widetilde{y}_{RB} = (9.49, 0.78, 1.113) + (-3.75, 0.082, 0.009) \otimes \widetilde{x} + (0.008, 0.0004, 0.003) \otimes \widetilde{x}^2 . \quad (8)$$

Here two fuzzy bands are drawn for two fuzzy models with their corresponding left points, centers and right points respectively.

An interesting feature can be observed from Figure 1 that there is a reverse nonlinear trend of zinc content in blood for normal and radiation workers. For normal people, it initially increases slowly with TOE upto around 20 and after that starts decaying rapidly. But in case of radiographers, it firstly starts decreasing rapidly with TOE upto around 20 and after that seems to increase. This graphical representation also matches with the expert's intention.

Case (ii): Zinc Content in Radiographer's Hair

See Table 4.

Therefore the actual least-squares estimates of the fuzzy parameters for normal persons and radiographers are computed given on Table 5.

The negative spreads are reformulated to compute the estimated fuzzy number according to Yang et al. Hence the fitted fuzzy regression model for normal person's hair is

$$\widetilde{y}_{NH} = (148.35, 7.73, 8.59) + (2.24, 0.5, 0) \otimes \widetilde{x} + (-0.076, 0, 0.024) \otimes \widetilde{x}^2 . \quad (9)$$

Normal person	Radiographer
$\hat{m}_{a_0} = 148.35$; $\hat{\alpha}_{a_0} = 7.73$; $\hat{\beta}_{a_0} = 8.59$;	$\hat{m}_{a_0} = 144.2$; $\hat{\alpha}_{a_0} = 0.48$; $\hat{\beta}_{a_0} = 12.44$;
$\hat{m}_{a_1} = 2.24$; $\hat{\alpha}_{a_1} = 0.499$; $\hat{\beta}_{a_1} = -0.379$	$\hat{m}_{a_1} = 17.38$; $\hat{\alpha}_{a_1} = 8.23$; $\hat{\beta}_{a_1} = 5.36$;
$\hat{m}_{a_2} = -0.076$; $\hat{\alpha}_{a_2} = -0.003$; $\hat{\beta}_{a_2} = -0.24$	$\hat{m}_{a_2} = -0.604$; $\hat{\alpha}_{a_2} = -0.217$; $\hat{\beta}_{a_2} = -0.14$

Table 5: The least squares estimates of the model

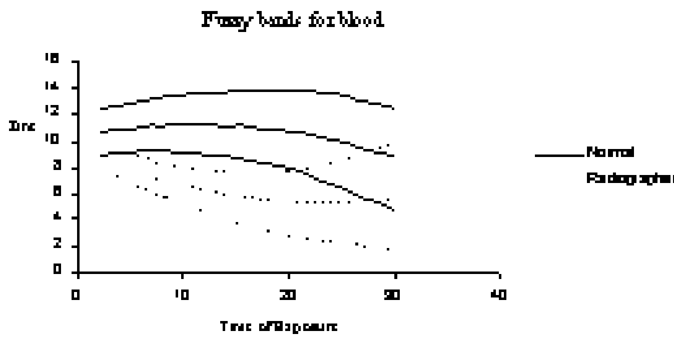

Figure 2:

Similarly the fitted model for radiographer's hair is

$$\widetilde{y}_{RH} = (144.2, 0.48, 12.44) + (17.38, 8.23, 5.36) \otimes \widetilde{x} + (-0.604, 0.14, 0.22) \otimes \widetilde{x}^2 \,. \quad (10)$$

From the above graphs, it can be said that the zinc content in radiographer's hair behaves in nonlinear fashion i.e., the zinc content increases upto around 25 years age and then steadily decreases with time of exposure. On the other hand the same in case of normal person seems to be linear, i.e., the zinc content in normal person's hair does not differ much as compared to radiographers.

5. Discussion

The imprecision is characterized within the fuzzy mathematical paradigm. Is the effect of chronic low dose radiation beneficial (hormetic) or hazardous? Researchers differ in this regard but we cannot deny the poorness of the low dose radiobiological data especially with respect to long period of studies. Major application of linear mathematical tools in the analysis of such biological events also failed to resolve the problem. The present study significantly reveals the fuzzy trend of vital bioelement like zinc in blood and hair of medical radiographers. The nature of the fitted fuzzy curve for radiation workers is parabolic in nature. it is observed from Figure 1 that radiographer's blood zinc content exhibits an opposite trend to that of normal person. Initially the curve starts decreasing and attends stability. In case of hair, there is much of fluctuation in radiographer's zinc content, which initially shows increasing behaviour followed by decreasing trend. In contrast to the normal, this shows more or less stability of zinc with TOE. No doubt the data set is small but interesting application of fuzzy trend analysis gives meaningful interpretations of the observations. A large data set with detailed information will enable us to achieve more accuracy in interpreting the low-dose radiation affects on human subjects as well as in establishing the zinc as low dose radiobiological biomarker.

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APPENDIX

A	B	C	D	E	F	G
27	1	2	143.2	149.4	10.5	9.6
27	1	2.25	141.1	150.3	11.1	10.2
27	1	2	146.3	151.1	12.6	11.3
27	1	2.5	149.5	146.2	10.9	10.2
27	1	2.25	141.3	153.2	12.1	11.3
27	1	2.25	161.4	163.3	10.3	9.4
27	2	2.5	156.3	143.1	11.6	10.3
27	2	2	160.2	152.2	9.3	9.8
27	2	1.75	149.4	141.2	12.2	10.6
30	1	5	165.3	276.9	10.5	7.5
30	1	4.75	162.1	197.8	11.1	5.8
30	1	5.5	160.3	208.3	12.6	7.1
30	2	5	159.4	207.3	10.2	6.2
30	2	4.75	149.3	270.6	10.9	6.3
30	2	5.25	159.4	290.3	10.7	6.4
30	1	5	166.3	280.5	12.4	6.5
30	1	5	162.1	244.4	11.6	5.3
30	1	5	159.4	234.5	11.8	5.6
30	1	4.5	165.5	236.6	10.3	6.1
33	1	7	165.9	383.1	11.5	6.9
33	2	7	144.4	270.9	10.1	7.1
33	1	8	159.3	280.4	9.4	7
33	1	8	164.9	290.3	12.1	7.4
33	1	7.5	170.3	199.3	10.3	6.3
33	1	8	154.9	244.4	9.1	5.2
33	1	8	161.2	259.3	12.6	5.9
35	1	10	171.3	263.4	11.3	6.1
35	1	10	173.1	293.1	9.9	5.3
35	1	10.5	159.4	259.2	10.4	7
35	1	10	155.3	340.3	11.6	5.5
35	1	9	159.4	189.4	12.1	7
35	1	9.5	169.3	192.1	9.8	5.9
35	1	9.5	170.5	179.4	12.2	6.2
40	1	15	162.4	262.6	11.2	7.5
40	1	14	170.6	260.6	10.5	5.8
40	1	15	160.5	190.5	9.9	7.1
40	1	14	161.7	262.8	12.5	6.2
40	1	15.5	159.6	238.9	12.1	6.3
40	1	14.5	167.6	250.7	11.3	6.6
40	1	14.5	170.5	242.6	10.8	5.3
40	1	15	160.7	282.6	12.4	5.5
40	1	16	152.6	271.1	11.1	6.5
40	1	14.5	161.7	302.6	11.3	5.9
45	1	20	150.3	218.8	9.2	7.2
45	1	21	161.3	210.6	9.6	6.9
45	1	20.5	172.4	90	10.9	7
45	1	19	177.8	265.8	10.5	6.2
45	1	21.5	180.2	141.1	11.3	6
45	2	19.5	181.3	262.3	12.6	7.1
45	1	20	160	214.6	12.4	5
45	1	20	151.9	218.8	9.3	4.2
50	1	25	139.4	265.8	9.9	4.5
50	1	26	162.3	268.1	9.2	5.9
50	1	24	155.4	289	9.6	5.6
50	1	26	160.9	185	10.2	5
50	1	25	130.2	211.6	10.3	4.3
50	1	25.5	154.6	265.4	9.4	4.1
55	1	30.5	155.3	123.3	8.9	4.9
55	1	31.5	160.4	121.4	9.5	5.2
55	1	30	162.3	101.2	6.3	6.4
55	1	28	159.4	123.3	9.4	5
55	1	29.5	155.4	99.6	8.3	5.9
55	2	29	140.6	111.6	8.4	5.3
60	1	28	136.4	171.6	9.3	5.1
60	1	30	139.3	99.2	7.2	6.1
60	1	33	149.2	90.3	6.4	4.6
60	1	34	142.5	128.6	7.1	4.2
60	2	32	141.6	113.8	9.3	5
60	2	30	150.6	110.6	9.4	5.1

Notations: Column A-age;

Col B- sex male -1 female-2;

Col C-time of exposure to radiation in years;

Col D- Zinc content of control/normal persons's hair;

Col E- zinc content of radiographer's hair;

Col F- Zinc content of control/normal person's blood;

Col G- Zinc content of radiographer's blood.

Unit of Zinc content is in ug/g (microgram/gram).