Reducing Low Back Pain in Construction Works; A Fuzzy Logic Approach

Oluwole H. ADEYEMI *ahacoy@yahoo.com*
Department of Mechanical Engineering
Federal University of Agriculture
P.M.B., 2240, Abeokuta, Ogun State, Nigeria

Samuel B. ADEJUYIGBE *samueladejuyigbe@yahoo.com*
Department of Mechanical Engineering
Federal University of Agriculture
P.M.B., 2240, Abeokuta, Ogun State, Nigeria

Salami O. ISMAILA *ismailasalami@yahoo.com*
Department of Mechanical Engineering
Federal University of Agriculture
P.M.B., 2240, Abeokuta, Ogun State, Nigeria

Adebayo. F. ADEKOYA *lanlenge@gmail.com*
Department of Computer Science
Federal University of Agriculture
P.M.B., 2240, Abeokuta, Ogun State, Nigeria

Abstract

In this study, a fuzzy linguistic model was developed to reduce the risk of Low back Pain (LBP) in construction works. The primary objective was to develop a computer-based model for risk assessment capable of generating results which are comparable more efficient than those obtained manually by human experts' calculations. The expert system used fuzzy set theory to make decisions about the level of risk associated with selected worker. Posture at work, frequency of lift and weight of load were the three constituent elements of input used while the output is risk of LBP. The result of validation shows that there was a strong positive relationship between the calculated human experts' LBP risk and that of the model with correlation coefficient of 0.934. It can thus be concluded that though conventional mathematical modeling has been a recognized tool in ergonomic evaluation, a fuzzy model system also generate a very helpful results in, minimizing risk involved in construction tasks and, determining effective means of deploying personnel.

Keywords: Fuzzy, Expert, Back, Pain, Construction.

1. INTRODUCTION

Low back pain (LPB) is pain and stiffness in the lower back. It is usually caused when a ligament or muscle holding a vertebra in its proper position is strained [1]. Low back pain (LBP) is the most prevalent musculoskeletal disorders (MSDs) [2]. It is the most common disabling musculoskeletal symptom [3] and the most commonly reported on-site job-related MSDs [4].

Occupations most likely to experience LBP injury because of manual lifting include labourers, assemblers, carpenters, painters, bricklayers, plasterers, joiners and plumbers [5-7]. Oude [8] stated that, in a population of working construction workers, majority suffered from occasional or frequent musculoskeletal complaints. According to [9] complaints of the back and elbow were the most often reported among bricklayers during work and the majority of the construction workers believe that their complaints are work-related. Lower back complaints among bricklayers might be related to lifting and carrying [10]. Many construction workers believe that their LBP is caused by manually lifting of heavy loads during work time and most of them experience that they have little control to solve the causes of their problem [11]. It was earlier affirmed that greater workloads increase mechanical stress (and thus strain) to the cause of LBP [12]. There are a number of factors that may make a manual material task hazardous in construction work, particularly for the development of LBP; awkward posture, frequency of lift and load [13-16], uncomfortable working position, working too long without break, adverse working environment, psychosocial factors [17] were mentioned as potential risk factors. It was stated that many other medical problems can contribute to musculoskeletal disease [18].

Lifting index appears to be a useful indicator for determining the risk of LBP caused by manual lifting [19]. NIOSH Lifting Equation is valid job analysis method to predict risk for low back injury [20]. It is a tool for evaluating the physical demands of two-handed manual lifting tasks which consists of two equations: the recommended weight limit (RWL) and the lifting index (LI) for evaluating some specific manual lifting tasks. The computation of RWL required measurement and input of parameters that describe the task such as location of hands, frequency of lifting, type of hand coupling required for the task, work duration and weight of load lifted. The LI is defined as the ratio of the actual weight of the load (L) lifted divided by the RWL for the job (LI=L/RWL). It gives an estimate of the relative physical demand for the task. Lifting tasks with a LI greater than 1.0 pose an increased risk for lifting-related pain. If the magnitude of the LI increases: the level of the risk for the worker performing the job would be increased; and a greater percentage of the workforce is likely to be at risk for developing lifting-related LBP. LI greater than 3 was considered to have the highest risk [21-22].

To retain workers in the construction field, it is essential to select potentially effective intervention measures and prevent the workers from further physical deterioration [9]. According to [23], every (extra) ergonomics measure implemented for LBP prevention might be profitable.

1.1 The Aim and Objective of The Proposed Study

The objective of the proposed study is to develop a fuzzy rule based model for LBP risk evaluation which traditional methods are unable to offer effectively. The study aimed to find out;

i. If there is a significant difference between the LBP risks calculated by human experts and that predicted by the model.

ii. If there is any difference in assessment results between human experts opinions and that of the fuzzy logic evaluation technique.

2. MATERIALS AND METHODS

2.1 Fuzzy Set Theory

The focus of attention of this study is the reduction of LBP risk involved in construction work using fuzzy logic based expert system for risk assessment of tasks involving manual lifting. A fuzzy system is a static nonlinear mapping between its inputs and outputs. Application of fuzzy modeling to ergonomics is becoming popular. Among many successful attempts, [24] used fuzzy as a tool to minimizing MSDs in Lathe machine workers using two input variables (frequency of lift and lifting height). A fuzzy technique was applied by [25] to develop a model for evaluating fatigue using data from several estimators of fatigue. A combination of probability and fuzzy set theory were used by [26] to handle the uncertainties in health risk assessment. Fuzzy reasoning algorithm was adopted by [27] to assess and predict cumulative trauma disorders occurrence in workplace.

It is assumed that the fuzzy system has inputs $u_i \in U_i$ where i = 1, 2. . . n and outputs $y_i \in Y_i$ where i = 1, 2, . . .,m, as shown in Figure 1. The inputs and outputs are “crisps”. The fuzzification block converts the crisp inputs to fuzzy sets, the inference mechanism uses the fuzzy rules in the rule-base to produce fuzzy conclusions and the defuzzification block converts these fuzzy deductions into the crisp outputs [28].

According to [29], if X is a set serving as the universe of discourse, a fuzzy subset A of X is associated with a function which is generally called membership function. For each x, $m_A(x)$ indicates the degree to which x is a member of the fuzzy set A. This membership degree indicates the compatibility degree of the assertion "x is A".

$$\mu_A : \times \rightarrow [0,1] \quad (1)$$

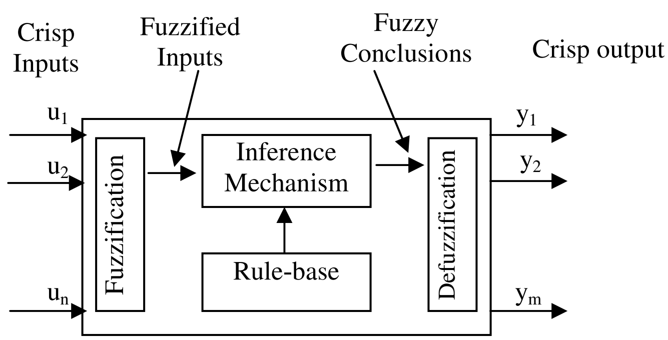

FIGURE 1: Fuzzy System Block Diagram [24].

If one assumes that A and B are two fuzzy subsets of X, their standard intersection, union and complement are also fuzzy sets given by:

$$\mu_{A\cap B}(\times) = \min[\mu_A(\times), \mu_B(\times)] \quad (2)$$

$$\mu_{A\cup B}(\times) = \max[\mu_A(\times), \mu_B(\times)] \quad \text{And} \quad (3)$$

$$\mu_{\underline{A}}(\times) = 1 - \mu_A(\times) \quad (4)$$

Where $\underline{A}$ is the negation of A (not A).

Intersection, union and complement defined above are fuzzy operators that one can use to combine fuzzy variables to form fuzzy expressions, as aggregating fuzzy rules.

In this study we used trapezoidal membership function for converting the crisp set into fuzzy set. Trapezoidal fuzzy numbers of the form (a, b, c, d) are more generalized form of membership functions and the most generic class of fuzzy numbers with linear membership function. The parameters a and d locate the "feet" of the trapezoid and the parameters b and c locate the "shoulders" [30]. This class of fuzzy numbers has more applicability in modeling linear uncertainty in scientific and applied engineering problems [31].

2.2 Study Site And Task Selection

2.2.1 Description of Study Area

Five construction sites located in the Southwestern Nigeria were used for the study. These included; the development of a factory along Ijoko road with 54,750 square meter area and a proposed ware house development at Agbara in Ota Local government area. Ado-Odo/Ota borders on metropolitan Lagos at 6°41′00″N 3°41′00″E / 6.6833333°N 3.6833333°E / 6.6833333; 3.6833333 to the north of the Area. The other three sites were situated in Abeokuta town. Abeokuta is the largest city and capital of Ogun State in southwest Nigeria. It is situated at

WikiMiniAtlas 7°9′39″N 3°20′54″E / 7.16083°N 3.34833°E / 7.16083; 3.34833 Coordinates: 7°9′39″N 3°20′54″E / 7.16083°N 3.34833°E / 7.16083; 3.34833, on the Ogun River; 64 miles north of Lagos by railway, or 81 miles by water.

The climatic conditions prevailing over the study areas in the ecosystems were mainly those of the tropical rainforest, typified by an average annual temperature 30 ± 100C, relative humidity of 65 ± 10% and an average annual rainfall of 1500±120mm [32].

2.2.2 Task Selection

Tasks for study were selected based on the following criteria:

- Manual lifting single-task performed regularly with at least 30 lift in a day
- Task performed for a long time without major changes in pattern
- Task that conform to the application of the RWL (i.e. which does not involve one-handed or seated lifting, handling unstable objects, none required of significant amount of non-lifting physical demands). Tasks including pushing, pulling, carrying, walking and climbing were not included in the study because they required significant energy expenditure.

Twenty nine lifting-related jobs were included in the study involving one hundred and twenty healthy male workers. Eight jobs were identified in the first construction site (CS) were workers lift concrete bricks weighing between 15 and 24kg. The lifting were identified in; brick setting, kerb setting, lowering bricks from truck bed, loading wheelbarrow with bricks (workers pushing wheelbarrow were not involved in the study). Another 7 jobs were identified in the second CS were workers lift concrete mortars during column/beams/slab filling task. The loads lifted typically weighed 25-30kg. Another 5 jobs were recorded in the third site. The weight of the material lifted ranges between 2.5 and 14kg. The jobs included lifting identified in fixing; window blade, ceiling fan, fluorescent holders and lifting steel to be cut into sizes on a cutting machine. Five jobs were discovered in the fourth site were workers were required to lift 2 - 7kg load. Jobs in this category included lifting during fixing of interlocking concrete pavers and tilling. Finally 4 jobs were recorded in the fifth CS and the load ranged between 5.5 and 42kg. The jobs included stacking/dis-stacking material into/from site store, lifting wooden doors.

2.3 Data Collection For Development of The Fuzzy Based Model

The data collection was conducted at the workers' workplace during the working period and at a time supported by the workers and the management. According to [33], reliable measurements are obtained if standardized measurement methods are used. For reliability, trained personnel were involved in the measurement of variables of the selected single-tasks. Workers were observed to record the task time. In each of the selected job the following variables were recorded: weight of the lifted object (kg) using a weighing scale, frequency of the lift (lift/min) with the use of stop watch, task duration (hour) with wrist watch, vertical and horizontal distances (cm) both at the origin and destination of the lift with meter rule, coupling rating by observation, asymmetry angle (degree) both at the origin and destination of the lift with the use of goniometer. Three sets of measurements were made for each worker and the frequency of lift was counted within the sample period of 15minutes.

For the purpose of validation, data obtained from the workers were used for the calculations of single-task lifting index. All the tasks were analyzed both at the origin of lift and at the destination. This is to obtain maximum possible values of LI for the jobs. Since there is no procedure for computing the LI for jobs with extreme variability, in jobs which the frequency of lift exceeded 10lift/min, a minimum LI value was computed for the critical case since above this value the frequency multiplier is set to zero and LI approaches infinity hence may not be used to distinguish between tasks. This procedure was also used for tasks in which the horizontal height exceeded 63cm. However doing this may result into an underestimation of risk involve in the task.

2.4 Techniques of The Proposed Fuzzy Logic Expert System

One of the shortcomings of the traditional evaluation methods is the insufficient information about what criteria used for the 'final result' [34]. This fuzzy approach of LBP evaluation will allow a more realistic modeling of variable status for output result and assists in determining the exact degree of a particular concept use for decision making by the users.

Low back Pain risk evaluation with the proposed fuzzy based model comprised with three steps:

1. Identification and Fuzzification of LBP risk factors and output risk value.

2. Formation of linguistic rules and inference mechanism.

3. Defuzzification of LBP risk value.

Step 1:- Three major lifting task risk factors; weight of load lifted (kg), posture at lift (asymmetric) (degree) and lifting frequency (lift/min) were selected as input variables for the model. The choice of these variables agreed with the view of [14-15] who identified these factors as the prominent risk factors in manual material lifting in the construction works. These variables were operationally defined as described in the revised NIOSH lifting equation. The classifications of the variables (Tables 1-2) were derived by finding the k-th percentile of values in the range of multipliers provided in the revised NIOSH lifting equation [35] for asymmetric and frequency. The same technique was adopted in the classification of load variable (Table 3) using a modified version of the study results relating linguistic terms and amount of load handled reported by [36].
The model was developed from an expert knowledge, who detailed five linguistic values to the variable Asymmetric: Extremely high deviation (EHD), Very high deviation (VHD), High deviation (HD), A little high deviation (AHD), Low deviation (LD).

K-th Percentile	Class Mid-point	Linguistic Term	Interval
0	0	Low deviation (LD)	0, 0, 1, 32.8
25	33.8	A little high deviation (AHD)	1, 32.8, 34.8, 66.5
50	67.5	High deviation (HD)	34.8, 66.5, 68.5, 100.3
75	101.3	Very high deviation (VHD)	68.5, 100.3, 102.3, 127.3
95	128.3	Extremely high deviation (EHD)	102.3, 127.3, 135.0, 180

Modified version of the range of asymmetric multipliers provided in the revised NIOSH lifting equation by [35].

TABLE 1: Fuzzy Set of Input Variable 'Posture'.

Five linguistic values to the variable Frequency of lift: Excessive high frequency (EHF), Very high frequency (VHF), High frequency (HF), Moderate frequency (MF), Low frequency (LF).

K-th Percentile	Class Mid-point	Linguistic Term	Interval
0	0.2	Low freq.(LF)	0, 0.15,0.25, 1.5
25	2	Moderate freq. (MF)	0.25, 1.5, 2.5, 4.5
50	5	High freq.(H)	2.5, 4.5, 5.5, 7.5
75	8	Very high freq.(VHF)	5.5, 7.5, 8.5, 10.5
100	>11	Extremely high freq.(EHF)	8.5, 10.5, 15, 15

Modified version of the range of frequency multipliers provided in the revised NIOSH lifting equation by [35]

TABLE 2: Fuzzy Set of Input Variable 'Frequency'.

Five linguistic values to the variable Load: extremely heavy load (EHL), heavy load (HL), moderate load (ML), light load (LL), and negligible load (NL).

K-th Percentile	Class Mid-point	Linguistic Term	Interval
0	0	Negligible load(NL)	0, 0, 0.5, 3.5
25	4.5	Light load(LL)	0.5,3.5, 5.5, 13
50	14	Moderate load (ML)	5.5, 13, 15, 31
75	32	Heavy load (HL)	15, 31, 33, 55
100	56 and above	Extremely heavy load (EHL))	33, 55, 110, 110

Modified version of the study results relating linguistic terms and amount of load handled by [36]

TABLE 3: Fuzzy Set of Input Variable 'Load'.

The consequence of the model is the risk of LPB. The experts [19] considered five linguistic values (Table 4) for the classification: No risk (NR), Low risk (LR), Medium risk (MR), high risk (HR) and Extremely high risk (EHR).

Range	Linguistic Term	Interval
0	No Risk (NR)	0,0,0,0
0-1	Low Risk (LR)	0,0,1,1.1
1-2	Medium Risk (MR)	1,1.1,2,2.1
2-3	High Risk (HR)	2,2.1,3,3.1
>3	Very High Risk (VHR)	3,3.1,5,6

Modified experts' opinions reported by [19].

TABLE 4: Fuzzy Set of Output Variable 'LBP risks'.

Step 2:- With the three inputs and five linguistic values for each, there are 125 rules (all possible combinations of premise linguistic values) used for the model. Some of the rules are stated below;

If (Posture is LD) and (Frequency is LF) and (Load is NL) then (Risk-of-LBP is NR)

1. If (Posture is LD) and (Frequency is HF) and (Load is NL) then (Risk-of- LBP is LR)
2. If (Posture is AHD) and (Frequency is MF) and (Load is NL) then (Risk-of- LBP is LR)
3. If (Posture is LD) and (Frequency is EHF) and (Load is NL) then (Risk-of- LBP is MR)
4. If (Posture is VHD) and (Frequency is LF) and (Load is NL) then (Risk-of- LBP is MR)
5. If (Posture is AHD) and (Frequency is HF) and (Load is LL) then (Risk-of- LBP is HR)
6. If (Posture is HD) and (Frequency is HF) and (Load is LL) then (Risk-of- LBP is HR)
7. If (Posture is HD) and (Frequency is HF) and (Load is LL) then (Risk-of- LBP is HR)

“ “ “ “

125. If (Posture is HD) and (Frequency is EHF) and (Load is LL) then (Risk-of- LBP is VHR)

The procedure of the fuzzy linguistic model, given three of the above inputs for any category of the workers, consists of calculating the membership degree of these values in all fuzzy sets of the input variables.

Step 3:- The risk of LBP is determined by inference of the fuzzy rule set, using Mamdani’s inference and centroid defuzzification of the fuzzy output. Mamdani's method was proposed in 1975 by Ebrahim Mamdani and it is the most commonly seen fuzzy methodology. The technique is intuitive, has widespread acceptance and is well suited to human input [30, 37]. Centroid defuzzification method was developed by Sugeno in 1985. It is also the most commonly used technique and it is been proved to be very accurate [38].

3. RESULTS AND DISCUSSIONS

One hundred and twelve (93.3%) of the 120 workers that participated in the study completed the questionnaire all of which have spent not less than 2 years on the current job. The demographics of the workers who participated in the studies are presented in Table 5.

	Mean	**SD***	**Range**
Age (yrs)	36.87	5.76	26-49
Duration of employment	5.87	2.49	2-12

*SD= Standard Deviation.

TABLE 5: An Overview of The Demographic Information of The Workers Studied In Five Construction Sites (n=112).

The model was run on Matlab 7.8 using several values of the input variables to obtain the results of the mapping of the system. Figure 2 to 5 showed the membership function graphs which display for inspection and modification of all the membership functions associated with all of the input and output variables for the entire fuzzy based model inference system.

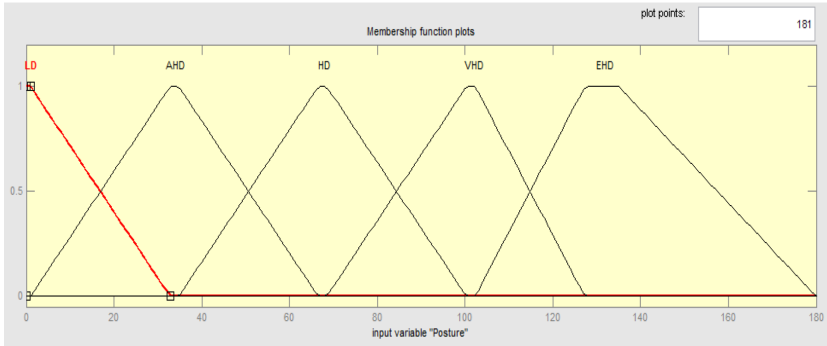

FIGURE 2: Membership function editor describing all membership functions for the input variable 'Posture'.

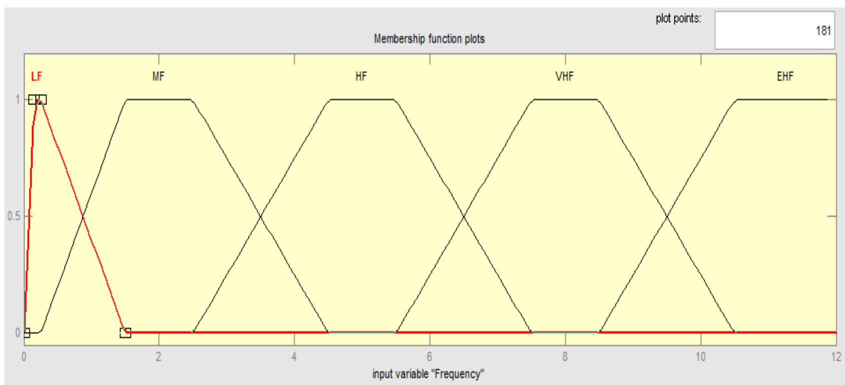

FIGURE 3: Membership function editor describing all membership functions for the input variable 'Frequency of Lift'.

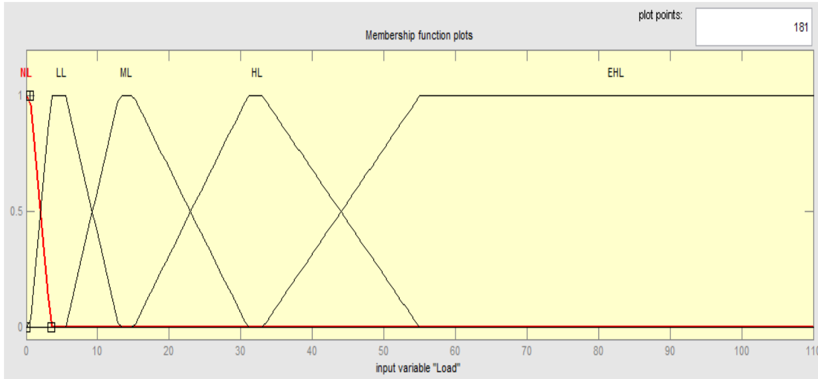

FIGURE 4: Membership function editor describing all membership functions for the input variable 'Load'.

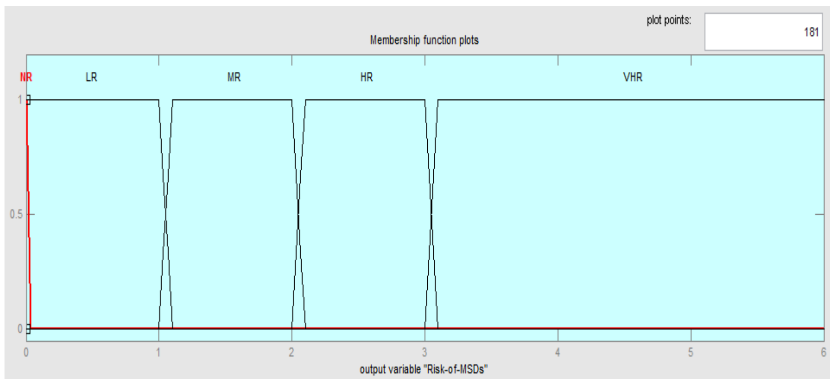

FIGURE 5: Membership Function Editor describing all membership functions for the input variable 'LBP-risk' .

Figure 6 and 7 are presentations of the surface viewers for plots of two variables which enables viewing the model as it varies over the ranges of its variables. The surface viewer examines the output surface of the fuzzy inference system for two inputs at a time. The two input variables assigned to the two input axes (X and Y) with the output variable on Z axis to display the result of calculation and the plot. The constant value associated with unspecified input is supplied in the reference input section.

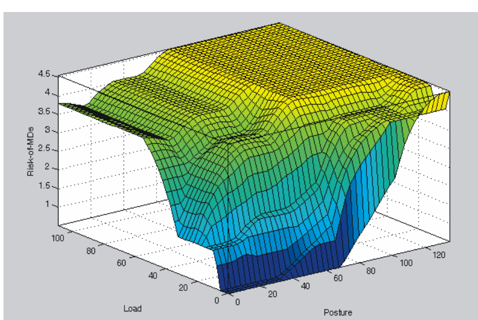

FIGURE 6: Surface found by mapping of the fuzzy based model (with variables posture, load and a reference point of 2.2 for frequency of lift).

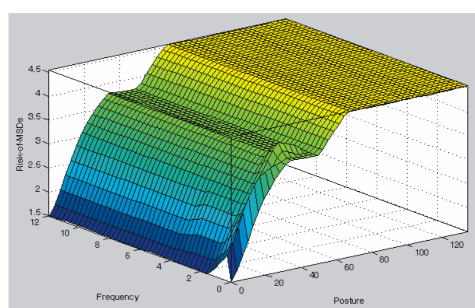

FIGURE 7: Surface found by mapping of the fuzzy based model (with variables frequency, posture and a reference point of 17.5kg for load).

3.1 Model Validation

In order to test the robustness of the model, twenty samples out of the antecedent variables recorded for all the workers were extracted (as presented in Table 6). The values range from LI<1 to LI>3. These model values were compared with the human expert calculated values using the human expert opinion which divided LI into five categories: LI=0 (No risk), LI=0-1(low risk), LI=1-2 (medium risk), LI= 2-3 (high risk) and LI= greater than 3 (Very high risk) [19].

Sample	Load (Kg)	Freq. (Lift/min)	Posture (Degree)	RWL	LI (Expert Value)	Model Value
1	24	1.3	35	6.8	3.53	3.57
2	24	2.1	55	5.74	4.18	3.74
3	24	1.1	45	5.3	4.53	3.57
4	2	1.9	40	4.06	0.49	0.76
5	8	3.2	0	7.89	1.01	1.28
6	10	3.8	0	7.31	1.37	1.52
7	24	1.5	10	11.1	2.16	2.55
8	24	2	45	6.09	3.94	3.57
9	28	1.9	10	11.47	2.44	2.48
10	28	8.8	30	5.49	5.1	3.64
11	26	2.1	35	7.84	3.32	3.65
12	6	5.0	30	2.23	2.69	2.33
13	11	0.5	30	6.82	1.61	1.8
14	12	0.8	50	6.37	1.89	1.87
15	28	2.6	50	6.04	4.64	3.67
16	2.5	0.3	40	7.54	0.33	0.57
17	7	0.1	65	7.09	0.99	1.0
18	15	1.3	60	5.15	2.92	2.34
19	24	2	25	7.56	3.17	3.31
20	22	1.8	30	5.44	4.04	3.27

TABLE 6: Operations studied, data recorded, expert calculated risk value and model risk values for twenty healthy male construction workers.

Figure 8 is a multiple line graph which records individual data values of human experts' calculated values and fuzzy model values as marks on the graph. The changes from point to point are visible. The major divergence of human experts' prediction from the model values were recorded in sample 10 where the human experts' calculated risk value was 5.1 while that of the model was

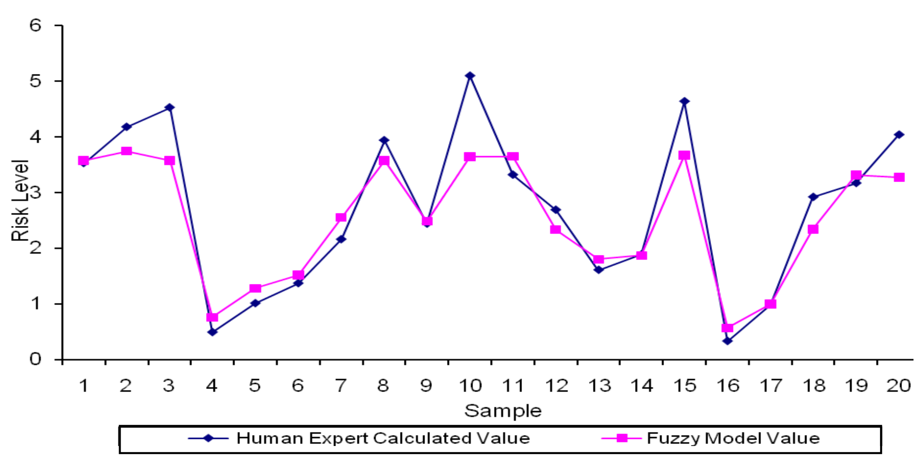

FIGURE 8: Comparing the calculated risk of human experts' value and the fuzzy based risk value.

3.64. The objective of the model is not to calculate the magnitude of lifting index value but to assess the risk involved in the task. The model predicted a very high risk (VHR) to any value greater than 3.0 which is also similar to the human expert's opinion which classified lifting index of 5.1 as VHR.

The Spearman correlation coefficient of the two sets of variables run on SPSS 16 was found to be 0.934. While comparing the means of the two sets using Independent Samples-T test at the confidence interval of 95%, the P- value for 2 tails was 0.637. The value indicates that there is not a statistically significant difference in the means of the two independent variables. Therefore the null hypothesis which stated that there is no significant difference between the calculated risks of human experts and the fuzzy model is accepted. The consequence of the validation however shows that there is a strong positive relationship and association between the two sets of variables.

In the fuzzy based LBP risk evaluation approach, one element can fit into two or more assort with different membership degree. The grade of membership expresses the degree of strength with which a particular element belongs to a fuzzy set, thus allowing a more realistic modeling of variable status and assists in determining the exact degree or level of a particular concept. Unlike the ordinary set theory which is governed by binary principles such that a variable either belongs to a set, which would indicate a membership value of 1, or it does not belong to the set and maintains a membership value of 0. The fuzzy approach also considered inherent uncertainties of the classification process, such as in the classification of a frequency of lift with 2.5 and another one with 2.6, who are relegated as MF (moderate frequency) and HF (high frequency) respectively. In this fuzzy approach, these frequency values (2.5 and 2.6) simultaneously fit into MF and HF with some membership.

The model provided good results when compared with the values obtained from human experts' calculations. It shows that the fuzzy sets theory can be a valuable tool that has encouraging results in bridging the gap between human-based and computer-based calculations of LBP risks among construction workers. It provides a model structure that requires the managers to make explicit decisions that will minimize lifting related risk among workers especially in construction jobs.

It is natural to expect that the fuzzy model could be improved with the introduction of new variables. Inclusion of variables such as personal factors (e.g anthropometry), indirect risk factors (e.g temperature, worker characteristics) is therefore becoming one of the future challenge and should be encouraged.

4. CONCLUSION

A fuzzy knowledge model was adopted to evaluate LBP risk from a set of three potential risk factors and have shown that the model can assist in assessing the risk in construction workers most especially for tasks that conform to the application of NIOSH lifting equations and provides a structure that enhances the administrators' denotative opinions. The outcome of the validation procedures shows that the adopted fuzzy model was capable of generating results of the same quality as the ones provided by human experts. Through the model, an improvement in the methods of efficiency in risk assessment was achieved. The model can help to reduce the risk associated with manual material lifting and to determine the effective means of deploying personnel in construction works.

5. REFERENCES

1. G.C. Phyllis. "Low Back Pain". McKesson Health Solutions LLC. Internet: www.cumc.columbia.edu/student/health/pdf/I-L/Low%20Back%20Pain.pdf. [Nov. 19, 2012].

2. Q.A. Louw, L.D. Morris1 and K. Grimmer-Somers. "The Prevalence of low back pain in Africa: a systematic review". BMC Musculoskeletal Disorders, vol. **8(**105), doi:10.1186/1471-2474-8-105, 2007.

3. J.W. Frymoyer, M.H. Pope, J.H Clements, D.G.Wilder, B. MacPherson, T. Ashikaga. "Risk factors in low-back pain". Journal of Bone and Joint Surgery, vol. 65, pp. 213-218, 1983.

4. A. Linda, Merlino, C. John, D.A Rosecrance, M.Thomas, "Symptoms of Musculoskeletal Disorders among Apprentice Construction Workers". Applied Occupational and Environmental Hygiene. College of Public Health, The University of Iowa, Iowa City, vol. 18(1) pp. 57–64, 2003.

5. European Agency for Safety and Health at Work (EASHW). "Building in Safety - Prevention of risks in construction in practice". European Construction Safety Summit. Euskalduna Conference Centre, Bilbao, Spain, Issue 108, 2004.

6. N.K. Akinomayowa. "Reducing repetitive strain and back pain among bricklayers" In: Buckle, P. (Ed.). Musculoskeletal Disorders at Work. London. Taylor and Francis, vol. 1, pp. 189-193, 1987.

7. National Institute for Occupational Safety and Health (NIOSH). "Work Practices Guide for Manual Lifting (WPG)", NIOSH Technical Report. U.S. Department of Health and Human Services, National Institute for Occupation, pp. 81-122, 1981.

8. H.K. Oude, B.M. Blatter, G.A. Geuskens, L.L. Koppes, P.M. Bongers. "Factors associated with the ability and willingness to continue working until the age of 65 in construction workers". Int Arch Occup Environ Health.vol. 85(7), pp. 783-90, 2012.

9. F. Henk, M. Vander, K.S.Judith, H.W. Monique. "Musculoskeletal disorders among construction workers: a one-year follow-up study" BMC Musculoskeletal Disorders vol, 13 pp.196, 2012.

10. E.W. Bakker, A,P. Verhagen, T.E. Van, C. Lucas, B.W. Koes. "Spinal mechanical load as a risk factor for low back pain: a systematic review of prospective cohort studies". Spine. vol. 34(8). E281-93. doi: 10.1097/BRS, 2009.

11. F. Lotters, A. Burdorf, J. Kuiper, H. Miedema, "Model for the work-relatedness of low-back pain". Scand.J Work Environ Health. vol.29, pp. 431-40, 2003.

12. D.B. Chaffin, G.B. Anderson. "Occupational Biomechanics" New York, John Wiley and Sons. 1991.

13. B.R. Da-Costa, V.E. Ramos. "Risk factors for work-related musculoskeletal disorders: a systematic review of recent longitudinal studies". American Journal of Industrial Medicine, vol. 53 (3), pp. 285-323, 2010.

14. Government of Western Australia Department of Commerce Code of Practice (GWADCCP). Manual Tasks. Internet: www.docep.wa.gov.au/worksafe/PDF/.../Code_manual_handling. Nov. 26, 2012 [Nov. 27, 2012].

15. S. Lenore, J.P. Azaroff, P.William, P. Elise, R. Rick, R. Cora. “Addressing work-related injuries and illness: a guide for primary care providers in Assachusetts”. Massachusetts coalition for occupational safety and health (massCOSH). (617) 825-SAFE, 2004.

16. T. Sturmer, S. Luessenhoop, A. Neth, M. Soyka, W. Karmaus, R.Toussaint, T.R. Liebs, U. Rehder. “Construction work and low back disorder. Preliminary findings of the Hamburg construction worker study”. Spine, vol. 22 (21), pp. 2558-2563, 1997.

17. Institution for Occupational Safety and Health (IOSH). “MusculoSkeletal Disorders”. Internet: www.iosh.co.uk/books_and_resources/our_oh_toolkit/musculoskeletal_disorders.aspx. Sept. 5, 2012 2012, [Sept. 6, 2012].

18. National Institute of Arthritis and Musculoskeletal and Skin Diseases (NIAMS). “Back Pain”. Internet: www.niams.nih.gov/health_info/Back_Pain/back_pain_ff.asp. Sept. 8, 2009, [July 2, 2011].

19. T.R. Waters, S.L. Baron, L.A. Piacitelli, V.P. Anderson, T. Skov, M. Haring-Sweeney. The revised NIOSH lifting equation. A cross-sectional epidemiologic study. Spine, vol. 24(4), pp.386-94, 1999.

20. S. Boda, P. Bhoyar, A.Garg. “Validation of Revised NIOSH Lifting Equation and 3D SSP Model to Predict Risk of Work-Related Low Back Pain”. Proceedings of the Human Factors and Ergonomics Society 54th Annual Meeting – 2010, San Francisco, Sept. 27 – Oct. 1, 2010.

21. R. Michael “NIOSH lifting equations”: Q & A. Internet: www.ergoweb.com/news/detail.cfm?id=566. May 2, 2012 [July, 14, 2012].

22. T.R. Waters, M.L. Lu, L.A. Piacitelli, D. Werren, J.A. Deddens. “Efficacy of the revised NIOSH lifting equation to predict risk of low back pain due to manual lifting: expanded cross-sectional analysis”. J Occup Environ Med. vol. 53(9) pp. 1061-7, 2011.

23. R.H. Westgaard. “Work-related musculoskeletal complaints: some ergonomics challenges upon the start of a new century”. Appl. Ergon. vol. 31 pp. 569-80, 2000.

24. S. Aman, B.D. Gupta, A. Sneh, “Minimizing MusculoSkeletal Disorders in Lathe Machine Workers”. International Journal of Ergonomics, vol. 1(2) pp, 20, 2011.

25. L. Crumpton, P. McCauley-Bell, T. Soh, “Modeling overall level of fatigue using linguistic modeling and fuzzy set theory”. Applied Ergonomics. 1997.

26. M. Abdullah, and H. Tahir, “Modeling for Uncertainty Assessment in Human Health Risk Quantification: A Fuzzy Based approach”. International Environmental Modelling and Software Society (iEMSs). Fifth Biennial Meeting. David A. Swayne, Wanhong Yang, A. A. Voinov, A. Rizzoli, T. Filatova (Eds.) Ottawa, Canada. S.O. 05, 2011.

27. D.J. Fonseca, T.W. Merritt, G.P. Moynihan, “Fuzzy Set Theory for Cumulative Trauma Prediction. Department of Industrial Engineering, the University of Alabama, Tuscaloosa. Mathware & Soft Computing, vol 8, pp, 129-135. 2011.

28. M.P. Kevin. “Fuzzy Control”. Department of Electrical Engineering The Ohio State University. Addison Wesley Longman, Inc., pp. 123, 1998.

29. L. A. Zadeh. “Probability measures and fuzzy events”. Journal of Mathematical Analysis and Applications. vol. 23, pp. 421, 1968.

30. MathWorks. "Fuzzy logic toolbox user's guide (version 2)". Internet: www.mathworks.com/help/pdf_doc/fuzzy/fuzzy.pdf. July 2002. [Sept.12, 2011].

31. A. Bansal. "Trapezoidal Fuzzy Numbers (a,b,c,d): Arithmetic Behavior". International Journal of Physical and Mathematical Sciences, ISSN: 20101791, pp. 39-44, 2011.

32. J. S. Oguntoyinbo, O.O. Areola, M. Filani. "A Geography of Nigerian development" [2nd ed.] Heinemann Educational Books (Nig.) Ltd., Ibadan, Nigeria, pp. 45-70, 1983.

33. T. Waters, V. Putz-Anderson, A. Garg. "Application manual for the revised NIOSH lifting equation". Cincinnati, OH; DHHS (NIOSH) Publication no. 94-110, 1994.

34. S. Y. Ramjeet, P.S. Vijendra. "Modeling academic performance evaluation using soft computing techniques; a fuzzy logic approach". International Journal on Computer Science and Engineering (IJCSE), vol. 3(2), pp. 676-686, 2011.

35. T.R. Waters, V. Putz-Anderson, A. Garg, L.J. Fine. "Revised NIOSH equation for the design and evaluation of Manual lifting tasks". Ergonomics, vol. 36, pp. 749-776, 1993.

36. A. M. Genaidy, W. Karwowski, D. Christensen, C.Vogiatzis, N. Deraiseh, A. Prins. What is "heavy"? Ergonomics, vol. 41(4), pp. 420-32, 1998.

37. S. Sumathi and P. Surekha "Fuzzy Inference and Expert Systems" Taylor and Francis group, LLC, DOI: 10.1201/9781439809037-c7, pp 261–306, 2010

38. J. Yen, I.R. Langar. Fuzzy logic: intelligence, control and information. Upper Saddle River (NJ). Prentice – Hall, 1999.