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Modeling Sand-Shoveling Related Pain Risks with Fuzzy Logic

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Abstract

This study developed a fuzzy linguistic model to predict work-related pain in sand shovelling. The primary objective was to develop a knowledge-based economic tool for ergonomics risk assessment capable of predicting same opinions of injury as obtainable with workers' self narrated. The model used 81 possible "IF THEN" linguistic rules fired into Mamdani inference engine to make decisions about the rank of risk associated with sand shovelling task variables. Scoop per minute, length of scoop, shovel/load mass and throw span were the four inputs variables used with "Sand-Shoveling Pain (SSP) risks' as the output. Validation result shows that 70% of the model predictions opinions corresponded to that of the opinion interpretation of the self-narrated numeric pain rating (SNNPR) of the affected 120 workers. The model generated risk (MGR) values had statistically significantly higher level of predicted risk (mean=3.91, SEM=0.47) compared to SNNPR (mean= 3.6, SEM = 0.50), with t(38) = -0.449, p = 0.656 with 95% confidence interval for the difference (-1.71, 1.09). Pearson correlation coefficient of the MGR values and the workers' SNNPR values was found to be 0.73. The independent sample t-test result (p = 0.667) also indicated a no significant difference of means. The model which could be applied in any workplace where it is necessary to consider ergonomics of work method and/or workplace design for manual shovelling tasks, was able to achieve the targeted objectives hence quality of reality was attributed to it.

Keywords*:* fuzzy, pain, risk, sand, scoop, shovelling

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1. Introduction

Shoveling, a form of manual handling with the use of a purposely-built hand tools called shovel, has some level of hazards attached. When poor technique is adopted in shoveling much stress is placed on the body's muscles and joints causing back pain, neck pain and other related injuries (ICC, 2014). Several studies were carried out in shoveling tasks where authors reported soft tissue injuries as the most common among all other reported disorders (Véronique, *et al*., 2004; Ryan, *et al*., 2013; Kaj, 2014). University of Vermont (2011) mentioned heart attacks and back strain as well as muscle soreness as results of shoveling tasks.

Shoveling tasks sends on the average more than 11,000 adult and children to hospitals every year (Kelli, 2011). It was reported that U.S. hospitals treat an average of about 11,500 injuries and medical emergencies a year related to shoveling snow. Two-thirds of the injuries occurred in men and more than half of the injuries resulted from acute musculoskeletal exertion and nearly 7% from cardiac problems, such as heart attack (Ann, 2011). Mikaela (2011) also reported that around 195,100 Americans were treated in emergency rooms for snow shoveling-related incidences from 1990 to 2006.

In other to minimize fatigue and injury rate in shoveling related tasks, Canadian Centre for Occupational Health and Safety (CCOHS) (1999) outlined some shoveling tasks variables guidelines. The rate should not be more 15 scoops per minute, length of scooping should not be longer than 15 minutes, the total weight of shovel and sand should be between 5 and 7 kg, throw height should not exceed 1.3 meters, throwing distance should be around 1 meter and the shovel handle should come up to the user's chest.

There is the need to formulates an effective strategy to mitigate the potential for loss to injuries (Kypriadis and Hidek, 2007; Michelle, 2007) by proper assessment of the risks involve in shoveling tasks. Risk assessment considers whether the identified hazards can be eliminated or not and if the hazard cannot be eliminated, seeks to find out if there are protective measures that can control the risks (Vivian, 2011). Several efforts were made by different authors to develop model/expert system for risk assessment and/or management. Some of the techniques used are for approximating discrete-valued target functions which supports a strict Boolean data type (true/false type of data). Among several efforts in this direction, Aljaaf (2015) used C4.5 decision tree classifier to predict risk levels of heart failure. Paul *et al.* (2012) developed a tool which applied a decision tree for assessing effects from exposures to multiple substances. In an attempt to improve the implementation of weather-based disease risk models, Kim *et al*. (2007) used a spatial interpolation method.

However, fuzzy logic techniques show some advantages over, and a possible means of overcoming many limitations noted with, some risk assessment/ evaluation methods. In addition to its ability to allow available experts' knowledge to be included, fuzzy logic has a truth value that ranges in degree between 0 and 1. Elements in fuzzy set can overlap, so a given crisp value can belong to multiple fuzzy sets with different membership degrees in each set. It is therefore expected that conclusions based on fuzzy models is an optional way (Ramjeet and Vijendra, 2011; Shirleyann, 2002).

To mention few, Fonseca *et al*. (2011) used fuzzy reasoning algorithm to assess and predict cumulative trauma disorders occurrence in the workplace. Adeyemi *et al*. (2015) used fuzzy inference system to developed an expert system called musculoskeletal disorders – risk evaluation expert system (MSDs-REES), capable of assessing risk associated with manual lifting in construction works. Monish *et al*. (2015) designed a fuzzy expert system for calculating the health risk level of a patient with input variables blood pressure, pulse rate, SPO2, temperature, and blood sugar and risk level of the patient as output variable. Sari *et al*. (2012) developed expert systems for the assessment of low back pain using the skin resistance and visual analogue scale values as input variables. Maryam *et al*. (2012) developed an intelligence fuzzy system for asthmatic patients using five modules of respiratory symptoms, bronchial obstruction, asthma instability, quality of life and asthma severity as inputs with the degree of asthma severity as output. A Fuzzy Logic Expert System (FLES) for manual material lifting risk evaluation was developed by Adeyemi *et al*. (2013). The FLES used load (kg), posture (degree), and frequency of lift (lift/min) as inputs variables and lifting risk as output variable to mention a few.

Four main components are involved in the use of fuzzy logic: fuzzification, an inference, a fuzzy rule base, and defuzzification. The input fuzzy set is determined by the system designer to break down the complete range of possible input values into membership functions that are available for use. Several shapes for the membership function can be used, including trapezoidal, gaussian, and triangular. The most common and simplest to understand are trapezoidal and triangular shaped membership functions

(Salem, 2015; Mansoor *et al.*, 2010; Monish, 2015; Mayilvaganan, 2014; Smita *et al.*, 2013).

Application of fuzzy logic for assessment and/or management of risks in shoveling tasks is very uncommon. However, there is still need for more efforts to develop automatic and economical methods for risk assessment which will require less human involvement and be cost effective. Hence, the need for this study which aimed at developing a model capable of predicting the degree of sand shoveling related pain among workers in sand mine industry. The objectives are to: find out if the self narrated numeric pain ratings (SNNPR) by the affected workers is the same with the one predicted by the developed model and; provide ergonomics tool for risk assessment as an alternative to scarce ergonomics human expertise.

2. Materials and Methodology

2.1 Data Collection for the Model Development

In this study, a model for assessing sand shoveling-related pain is proposed with four input variables. These variables are the potential risk factors in manual shovelling task as highlighted by CCOHS (1999) and Bridger and Sparto (1998). These include scoop per minute, length of scoop, shovel-load mass and throw span. The output variable, sand shoveling pain (SSP) risk was determined by fuzzy logic.

2.2 Sand Shovelling tasks Variable Managament

2.2.1 Methods adopted to measure task variables are;

a. Scoop per minute: Tasks were observed as they were carried out. Numbers of scoops made by each subject were counted within a space of one minute using a stopwatch.

b. Length of scoop: Time spent (second) in scooping before break was measured using a stopwatch.

c. Shovel and Load mass: Shovel mass plus load mass (Kg) was measured randomly in four times, for each subject, using a digital weighing scale and the average value was computed.

d. Throw span: The horizontal distance (m) of the load from the origin to the destination was measured using a meter rule.

2.2.2 Measurements were recorded to the nearest tenth of a centimetre. All instruments were inspected before the commencement of measurement to ensure accuracy. The following are the descriptions of tools used for the measurements;

Tape rule: The tape rule was made of latex material and had calibrations in centimeter. Its flexibility allowed it to be used for different measurements. The tape rule had a range of 0-150cm.

The weighing scale: The weighing scale had a flat surface on which objects can stand. The capacity of the scale was 120Kg.

Digital stopwatch: Simply measured and displayed the time interval from an arbitrary starting point that began at the instant the stopwatch was started. It measured time interval by using a frequency source. Frequency is the rate of a repetitive event, defined as the number of events or cycles per second (Michael, 2002).

2.3 Personal Data Collection, Job Demand and Work Station Assessment

Personal data were collected from 120 male participants from 12 sand mine locations in Ifo, and Abeokuta, Southwest Nigeria, using a well-structured questionnaire for parameters such as, age, years of working experience on the current job, physical and health conditions. The questions were structured in a simple way and interpreted to workers in their local languages.

2.4 Assessment of Sand Shovelling-related Injuries

Numeric Rating Scale (NRS) tool was used for the assessment of body pain intensity. NRS is the most widely used pain intensity scales for adult. The tool asked workers to mention the painful regions of their body as a result of the current job and rate the pains by assigning a numerical value with zero (0) indicating no pain and 10 representing the worst pain. NRS are sensitive in assessing acute pains (Ellen, 2012; Breivik, 2000).

2.5 Data Analysis

Statistical Package for the Social Sciences (SPSS) Version 16.0 (SPSS, 2007) was used to analyze the collected data. Spearman's (rho) and Pearson's were used for significance tests of correlation coefficients values of NRS as narrated by workers and the ones predicted by the developed model. According to Gerstman (2006), correlation quantifies the extent to which two quantitative variables, "go together." Correlation strengths can be classified as weak correlation $0 < |r| < 0.3$, moderate correlation $0.3 < |r| < 0.7$ and strong correlation $|r| > 0.7$. For further confirmation, the independent sample t-test was used to evaluate the difference between the means of the two independent groups.

2.6 Sand Shoveling Risk Evaluation with Fuzzy Logic Model

Sand shovelling risk evaluation with fuzzy model comprised of three steps as shown in Figure 1.

1. Fuzzification of inputs task variables and output risk value.
2. Determination of application rules and inference method.
3. Defuzzification of risk value.

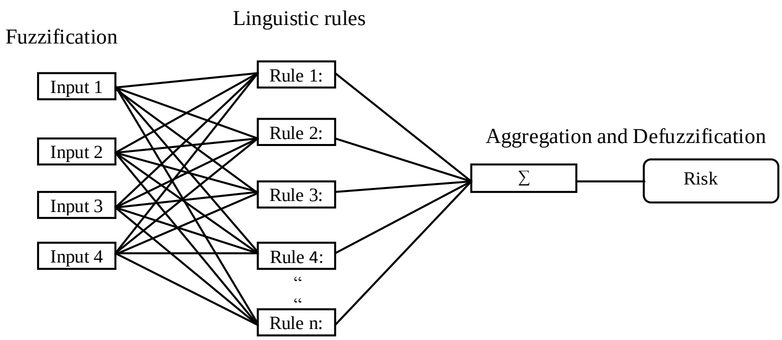

Figure 1. Fuzzy Inference for sand shoveling risk evaluation

2.6.1 Fuzzification of Sand Shoveling Task and Risk Value

Fuzzification was carried out using input variables and their membership functions of fuzzy sets. Fuzzification is the first step in the fuzzy inferencing process. This involves a domain transformation where crisp inputs (input variables) are transformed into fuzzy inputs Passino and Yurkovich (1997). Each worker had four input variables. Each input variable had three trapezoidal membership functions. The fuzzy sets of the input variables are presented in Tables 1, 2, 3 and 4. The system was developed from an expert knowledge, who detailed 3 and 4 linguistic values to each of the input variables and output variable respectively. The intervals were carefully formulated from the recommended values as stated by CCOH (1999) and as highlighted in Table 1. Using trapezoidal membership function (Figure 2), which is defined by a lower limit a, an upper limit d, a lower support limit b, and an upper support limit c, of which a < b < c < d all the four values were determined by same expert knowledge. For instance, in the case of Scoop per minute, the recommended rate was 15. Whenever the rate is higher than this value it is defined as "above normal rate". When it falls below 15, it is referred to as "below normal rate". The two figures at the flat top (d and c) which has a full membership function of 0.1 were carefully determined to ensure that either of the values do not go above the recommended (15) hence a range between 14 to a maximum of 15 were selected. This knowledge was embraced by three professionals in the field of ergonomics drawn from academics environment. The technique was used to determine intervals of other variables.

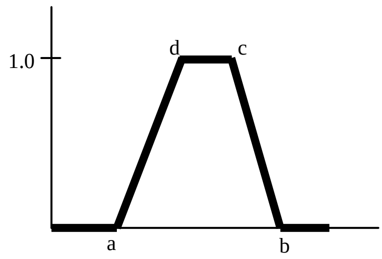

Figure 2. Typical Continuos Fuzzy Set Membership Function Trapezoidal

Table 1. Guidelines in shoveling to avoid fatigue and injury

Parameters	**Optimal Condition**
Rate	15 scoops per minute
Length of time	No longer than 15 minutes
Shovel and Load mass	The total weight should not exceed 5-7 kg
Throw Height	Not exceed 1.3 meters
Throwing Distance	Around 1 metre

(Source: Canadian Centre for Occupational Health and Safety, 1999)

The membership function graphs which display all membership functions associated with all of the input and output variables for the inference system are shown in Figures 2 to 6.

Table 2. Fuzzy Set of Input Variable ‘Scoop per minute’

Linguistic Term	Interval
Below Normal Rate (BNR)	0, 0, 13, 14
Normal Rate (NR)	13, 14, 15,16
Above Normal Rate (ANR)	15,16, 20,20

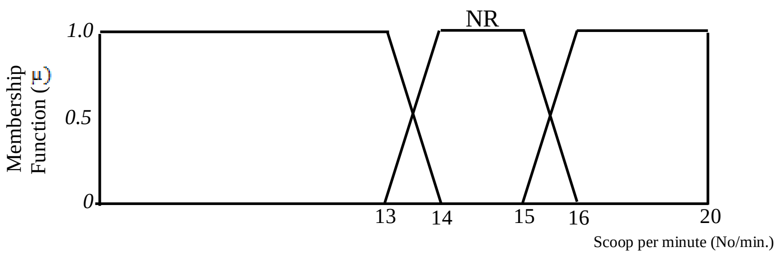

Figure 3. Membership function editor describing all membership functions for the input variable ‘Scoop per minute’.

Table 3. Fuzzy Set of Input Variable ‘Length of Scoop’

Linguistic Term	Interval
Below Normal Time (BNT)	0, 0, 13, 14
Normal Range of Time (NRT)	13, 14, 15,16
Above Normal Time (ANT)	15,16, 50, 50

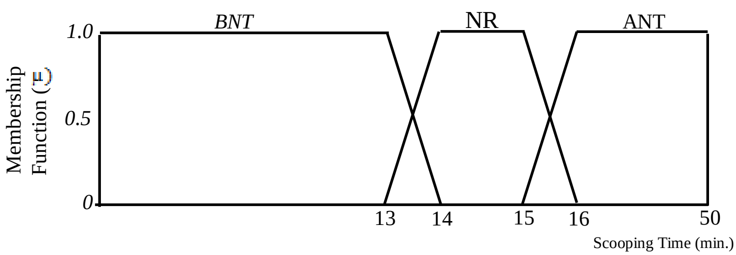

Figure 4. Membership function editor describing all membership functions for the input variable ‘Length of Scoop’

Table 4. Fuzzy Set of Input Variable 'Shovel-load Mass'

Linguistic Term	**Interval**
Mass Below normal (MBN)	0, 0, 4, 5
Normal Mass (NM)	4,5,7,8
Mass Above Normal(MAN)	7,8, 15,15

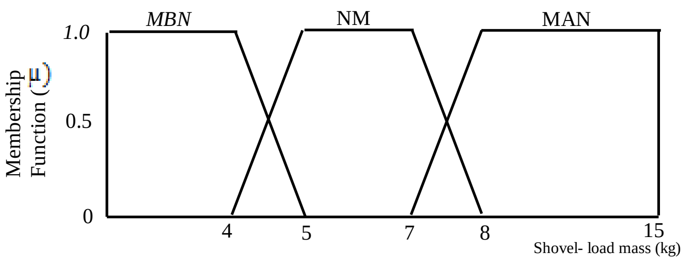

Figure 5. Membership function editor describing all membership functions for the input variable 'Shovel and Load mass'.

Table 5. Fuzzy Set of Input Variable 'Throw Span'

Linguistic Term	**Interval**
Short Span (SS)	0, 0, 0.6,0.8
Normal Span (NS)	0.6,0.8,1.0,1.2
Above Normal Span (ANS)	1.0,1.2, 4, 4

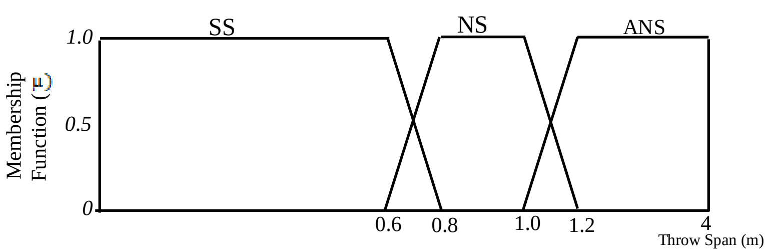

Figure 6. Membership function editor describing all membership functions for the input variable 'Throw Distance'

Table 6. Fuzzy Set of Output Variable 'Sand-Shoveling Pain (SSP) Risks'

Range	**Linguistic Term**	**Interval**
0	No Pain (NP)	0,0,0,0
1-3	Mild Pain(MP)	0,1,3,4
4-6	Moderate Pain(MRP)	3,4,6,7
7-10	Severe Pain (SP)	6,7,10,10

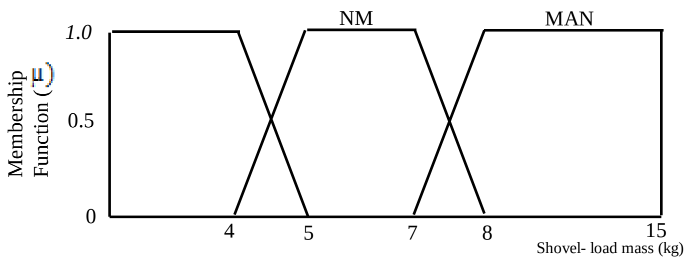

Figure 7. Membership function editor describing all membership functions for the output variable 'SSP-Risk'

2.6.2 Rural and Inference Generation

The rules used in this study were linguistic and in the form of "IF-THEN". According to Yager *et al*. (1989), fuzzy IF-THEN rules allow to evaluate good approximations of desired attribute values in a very efficient way. Fuzzy IF-THEN rules also allow available experts' knowledge to be included. The rules were used to formulate the conditional statements that comprise the complete knowledge base of the system. A single if-then rule assumes the form 'if x is A then y is B'. The if-part of the rule 'x is A' is the premise, while the then-part of the rule 'y is B' is the conclusion (Ajith, 2005).

To formulate the initial rule base, the input space was divided into multidimensional partitions and then actions were assigned to each of the partitions. The partitioning was achieved using one dimensional membership functions as shown in Table 6. The consequent parts of the rule represent the actions associated with each partition (Table 5). It is evident that the membership functions and the number of rules are related to the partitioning.

Hence with the four inputs and three linguistic values for each, there are at most 3^4 = 81 possible linguistic rules.

Table 7. Risk matrix table for assessment of shoveling related injury risks

Sand-Shoveling Pain Risks						**Throw Span**		
						SS	**NS**	**ANS**
Scoop per minute	BNR	**Length of Scoop**	BNT	**Shovel Load mass**	MBN	0,0,1,0,1,2,2,3,1	1,2,3,2,3,4,3,4,5	3,3,4,4,5,4,5,4,8
	NR		NRT		NM	1,2,3,2,3,4,3,4,3	3,3,4,3,3,6,5,6,8	4,5,6,5,6,6,6,8,9
	ANR		ANT		MAN	3,3,4,4,5,6,5,6,8	4,5,6,5,6,8,6,8,9	5,6,8,6,8,9,8,9,10

Using Table 7, the following ten (10) rules show only a portion of the 81 possible linguistic rules.

- Rule 1. If (ScoopPerMinute' is BNR) and (LengthOfScoop is STS) and (Shovel-LoadMass is MBN) and (ThrowSpan is SS) then (SSP-Risk is NP)

- Rule 3. If (ScoopPerMinute' is BNR) and (LengthOfScoop is STS) and (Shovel-LoadMass is MAN) and (ThrowSpan is SS) then (SSP-Risk is MP)

- Rule 27. If (ScoopPerMinute' is BNR) and (LengthOfScoop is ANT) and (Shovel-LoadMass is MAN) and (ThrowSpan is ANS) then (SSP-Risk is SP)

- Rule 29. If (ScoopPerMinute' is NR) and (LengthOfScoop is STS) and (Shovel-LoadMass is NM) and (ThrowSpan is SS) then (SSP-Risk is MP)

- Rule 30. If (ScoopPerMinute' is NR) and (LengthOfScoop is STS) and (Shovel-LoadMass is MAN) and (ThrowSpan is SS) then (SSP-Risk is MP)

- Rule 31. If (ScoopPerMinute' is NR) and (LengthOfScoop is NRT) and (Shovel-LoadMass is MBN) and (ThrowSpan is SS) then (SSP-Risk is MP)

- Rule 64. If (ScoopPerMinute' is ANR) and (LengthOfScoop is STS) and (Shovel-LoadMass is MBN) and (ThrowSpan is NS) then (SSP-Risk is MRP)

- Rule 65. If (ScoopPerMinute' is ANR) and (LengthOfScoop is STS) and (Shovel-LoadMass is NM) and (ThrowSpan is NS) then (SSP-Risk is MRP)

- Rule 80. If (ScoopPerMinute' is ANR) and (LengthOfScoopis ANT) and (Shovel-LoadMass is NM) and (ThrowSpan is ANS) then (SSP-Risk is SP)

2.6.3 Defuzzification of Risk Value

After completing the fuzzy decision process, the fuzzy value obtained was converted to a crisp value by the process known as defuzzification. A centre of area (centroid) technique reported by Padhy (2005) as one of the most common methods was adopted and this is presented in equation 1.

The centroid defuzzification technique can be expressed as

$$x^* = \frac{\int \mu_i(x)\, x\, dx}{\int \mu_i(x)\, dx}$$

...where x^* is the defuzzified output, $\mu_i(x)$ is the aggregated membership function and x is the output variable.

2.7 Model Implementation

The model was carried out in MATLAB (version 7.8) using several values of the input variables to obtain the result. MATLAB stands for MATrix LABoratory and the software is built up around vectors and matrices. It is a programming language which allows matrix manipulation, plotting of functions and data, implementation of algorithms and creation of user interfaces (Kristian, 2009). It was used across industry and the academic world for risk assessments (Richard, 2004).

2.8 Model Validation

In order to test the quality of the model, the variables recorded for all the subjects were run in the model. The model generated risk (MGR) values were recorded for each subject. Each of the values generated was interpreted based on the expert's opinion which divided sand shoveling pain risk into four categories using NRS pain intensity scales to obtain all the risk linguistic descriptions. The recorded MGR values were compared with the subjects' recorded SNNPR for significance tests of correlation coefficients strength using Spearman's (rho) while setting p-value at 0.01. The significant difference between the means of the two independent groups (MGRV and SNNPR) was also measured using independent-samples t-test at $p<0.05$. Though there is no consensus on the most appropriate metric for model errors, the root mean square error (RMSE) was used as a standard statistical metric to measure the model performance (Ken and Keke, 2011).

3. Results and Discussion

One hundred and fifteen (95.8%) of the 120 workers, all of which have spent not less than 2 years on the current job, participated in the study by completing the procedures and the questionnaire. The demographics of the workers are as shown in Table 8.

Table 8. Statistic of the demographic information for 120 workers studied from 12 sand mine locations in Ifo, and Abeokuta, Southwest Nigeria

Descriptions	**Age**	**Years of Working Experience**
Mean	25.4	2.2
Std. Deviation	4.8	0.95
Range	14-35	2-6

Table 9 presents 20 randomly selected workers, their corresponding measured shoveling task variables, the workers' SNNPR values, the MGR values and opinions/ interpretations of the combined effects of the input variables on the affected workers.

Correctness of predictions of the model opinion is noted with 14 (70%) of the model opinions corresponded with the interpreted opinions of the affected workers. However MGR over estimated the risks of 4 (20%) of the total predictions (cases 10, 12, 15 and 19) while the remaining 10% (case 2 and 4) predicted a lesser severity of "mild" as against "moderate" predicted by SNNPR. The mean value for SNNPR is 3.6 (2.1) while that of MGRV is 3.9 (2.2).

3.1 Model Performance Statistics Analysis Tests

3.1.1 Correlation Test

The Spearman's rho correlation coefficient of the two sets of variables was found to be 0.62 (moderate strength) while Pearson Correlation was 0.73 (strong strength). The p-value obtained (0.004 and 0.000 respectively) were below 0.01 and so there is confident of at least moderate correlation between the two sets of values generated by SNNPR and MGR. The coefficient of determination of 0.62 suggests 62% of variability.

Table 9. Task variables recorded, reported SNNPR and MGR values for randomly selected twenty healthy sand shovelers.

Sample	Scooping Rate	Scooping Time	Shovel Load	Throw Dist.	SNPR	Affected workers' Opinion	MGRV	Model Opinion
1	7	36	9	2.1	9	Severe	8.25	Severe
2	8	32	7	1.2	5	Moderate	2	Mild
3	9	15	5	0.9	3	Mild	2	Mild
4	8	10	4	0.7	4	Moderate	1.94	Mild
5	5	9	4.5	0.8	1	Mild	2	Mild
6	15	20	6	1	4	Moderate	5	Moderate
7	9	25	6.5	2.5	3	Mild	2	Mild
8	12	15	9	1.7	1	Mild	2	Mild
9	10	13	6	1.2	1	Mild	2	Mild
10	18	15	6	1.1	4	Moderate	6.65	Severe
11	20	11	8	1	4	Moderate	5	Moderate
12	15	30	6	1.2	5	Moderate	8.26	Severe
13	15	15	8	0.8	4	Moderate	5	Moderate
14	7	8	6	1	3	Mild	2	Mild
15	8	7	9	2	3	Mild	5	Moderate
16	6	21	5.5	0.9	4	Moderate	5	Moderate
17	7	13	7	0.7	3	Mild	1.94	Mild
18	5	12	6.5	1	1	Mild	2	Mild
19	6	13	8.5	1.1	2	Mild	3.5	Moderate
20	14	14.5	7.5	1.5	8	Severe	6.65	Severe
Mean Total					**3.6(2.1)**		**3.9(2.2)**	

Two hundred and nine (209) respondents representing 75.7% reported to have suffered pains in the last 12months, 147 (55.1%) in the last 1 month and 157 (58.8%) in the last 7days. All reported pains lasted for 24 hours with incurred medical bills. About 70% of this group of workers stated that the pains suffered prevented them from doing their normal works.

From Figure 2 and in descending other, 274 (99.3%) complained of Low back pain (LBP), 230 (83.3%) complained of shoulder pain, 166 (60.1%) reported wrist/hands pain, 92 (33.3%) complained pains in their ankle/feet, 83 (30.1%) complained of hip/thighs pains. Other reported pains included kneels (18.5%), neck (16.7%), upper back (14.1%), fingers (6.7%) and chest (5%).

3.1.2 Independent-samples t-test

The result of independent-samples t-test which appraises whether means for the two independent groups (SNNPR and MGRV) are significantly different from each other, found that MGR had statistically significantly higher level of predicted risk values (mean=3.91, SEM=0.47) compared to SNNPR (mean= 3.6, SEM = 0.50), with $t(38) = -0.449$, $p = 0.656$. However, the groups' means are significantly not different because the value of "Sig. (2-tailed)" is greater than 0.05. The 95% confidence interval for the difference is (-1.71, 1.09).

3.1.3 Root Means Square Error (RMSE)

The result of this test helps to provide a complete picture of the error distribution of the two sets of variables. In this case the mean of the 20 MGR values comes to 3.91, which is 0.31 higher than the mean of the SNNPR (3.6). Hence the MGR are biased 0.31/20 = 0.015 degrees too high than SNPR, indicating some degree of over prediction by MGR. Of the 20 SNNPR however, 8 (cases 1, 2, 3, 4, 7, 15, 17 and 20) had its values higher than that of the MGRV. However, there are no really large errors noted, the highest being the 3 degree error in case 2. Therefore the tally of the squares of the errors amounts to 51.56, leading to an RMSE of 1.61.

3.2 Discussion

In this study a fuzzy logic based model was adopted to evaluate sand shoveling pain risk based on four risk factors; scoop per minute, length of scoop, shovel-load mass and throw span, using 81 sets of IF-THEN rules. One of the advantages derived with the use of this approach is that, fuzzy rules of this format appeals to human perception without conscious reasoning, as they contain linguistic variables and linguistic terms for easier comprehension. For example stating that 'Scoop per minute' = "Above Normal rate", the risk involved in this statement is quite easy to understand rather than stating the exact values like 'Scoop per minute'= 16.

The model provided good results when the recorded task variables were run in the model. This is demonstrated in the randomly selected cases shown in table 9 where the risk values generated by the model were compared with the workers' SNNPR values. According to Ken and Keke (2011), accuracy in modelling is a function of bias and precision so that obtaining a more precise estimate without increasing bias implies that the model prediction is more accurate. The degree of bias (0.015) and RMSE level of 1.61 results obtained from table 9 provided a very respectable result for the model performance. However despite the recorded bias, the Spearman's rho correlation coefficient of 0.62 obtained shows that statistically the two variables, MGR and SNNPR values have good association. The model accuracy was further confirmed with the use of independent sample t-test which confirmed no significant difference of means. Hence, it can be said that the pain numeric ratings narrated by the affected workers have the same ranks with the ones predicted by the model.

When a model is successful at explaining happenings, it is attributed to it, and to the elements and concepts that constitute it, "the quality of reality" (Jones, 2011). The model had been shown to provide reliable result with proof of its correctness as 70% of the model predictions opinions corresponded to that of the opinions interpretation of the self narrated numeric rating rank of the affected workers.

The fuzzy approach in this study considered inherent uncertainties of the membership classification process, such as in the classification of a shovel-load mass (kg) with 7.4 kg and another one with 7.6 kg, which could be relegated both as NM (normal mass) and MAN (mass above normal) at the same time. These mass values (7.4 kg and 7.6 kg) simultaneously fit into the two membership functions but with different degree of memberships.

One other advantage of using this model is the non-changing generated opinions as against human judgements which could provide different opinions for risk severity related to the study task under the same condition depending on human feelings. The model offers some solutions to scarce expertise in the study area where human ergonomics experts scarcely exist to help offer useful information to workers and/or managers in the industry. It allows for quick and efficient decision making. It provides a model structure that requires the worker and/or managers in sand mine industries and other construction industries, where sand shoveling task is in practice, to make explicit determinations that will minimize task-related risks. It can also find its applications in any environments where it is necessary to consider work method and/or workplace design with respect to the ability of workers to perform manual shoveling tasks.

Improvement on the outcome of this study may include introduction of more variables such as anthropometry, working tools condition and other indirect risk factors like weather conditions. The fuzzy system can also be taught using neural network learning, EC, or other adaptation techniques for comparison of results.

However, there are a number of limitations that should be aware of for future efforts. The fact that posture nor competence of the individuals was not included within the analysis – yet forms a significant variable that should be covered. The medical condition of the individual should also be carefully assessed before they complete any questionnaire as existing neurological, muscular skeletal and vascular ailments may impact upon the results. It is however strongly recommended that a social sciences data collection instrument is not used in future work – unless perception can be better tied to hard facts and evidence. Hence this model is not the product of this work, rather it is the vehicle through which to deliver a product.

4. Conclusions

In this study a fuzzy logic based model was adopted to evaluate sand shovelling pain risk based on four risk factors of scoop per minute, scoop length, shovel-load mass and throw span. Arising from the findings, model generated risk (MGR) values had statistically significantly higher level of predicted risk values (mean=3.91, SEM=0.47) compared to the workers' self narrated numeric pain rating (SNNRP) values (mean= 3.6, SEM = 0.50), with $t(38) = -0.449$, $p = 0.656$. The 95% confidence interval for the difference is (-1.71, 1.09). The Spearman's rho and Pearson correlation coefficient of the MGR and the workers' SNNRP values were found to be 0.62 (moderate strength) and 0.73 (strong strength) respectively. The independent sample t-test result ($p = 0.667$) also indicated a no significant difference of means. 70% of the model predictions opinions corresponded to the opinions interpretation of the SNNRP ranks of the affected workers. The model provided a structure that requires workers and/or managers in sand mine industries, construction industries and workplace where it is necessary to consider work method and/or workplace design with respect to the ability of workers to perform safe manual shoveling tasks. Adopting this development will reduce injury related medical bills and enhance safety of concerned workers.

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