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A SHOVELING-RELATED PAIN INTENSITY PREDICTION EXPERT SYSTEM FOR WORKERS' MANUAL MOVEMENT OF MATERIAL

Adeyemi Hezekiah Oluwole[1*], Adefemi A. Adekunle [2], Akinyemi O. Olasunkanmi[1], Adefemi O. Adeodu[3]

[1] *Department of Agricultural and Mechanical Engineering, Olabisi Onabanjo University, Ago Iwoye, Nigeria*
[2] *Department of Mechatronics Engineering, University of Oye Ekiti, Nigeria*
[3] *Department of Mechanical and Mechatronics Engineering, Afe Babalola University, Ado-Ekiti, Nigeria*

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ABSTRACT

In this study, a fuzzy-based expert system called the Pain Intensity Prediction Expert System (PIPES) was developed to predict pain severity risk (PSR) in shoveling-related tasks. The primary objective was to develop a non-changing rating risk assessment ergonomics tool that both efficient and comparable with those obtained from human ergonomics experts in the field of application. PIPES used fuzzy set theory (FST) to make decisions about the level of pain associated with a selected worker base on the measured task variables, namely scooping rate, scooping time, shovel load, and throw distance as input and PSR as the result. Values obtained from variable measurements from a sand shoveling task were run with PIPES, and the results were compared with the workers' self-reported pain (WSRP) intensity using a numeric rating scale (NRS) tool. The result of validation showed that there was a strong positive relationship between WSRP NRS and PIPES NRS, with a correlation coefficient of 0.70. The independent sample t-test for mean difference showed that WSRP had a statistically significantly lower level of NRS (4.35 ± 2.1) compared to PIPES (4.75 ± 2.2), t (38) = - 0.591, p = 0.558. With a significance level of 0.001 at 95% confidence, the groups' means were not significantly different. The study developed an expert system, PIPES, which can be used as a computerized representation of ergonomics experts, who are scarce. PIPES can be applied to construction industries, sand mine locations, and any workplace where materials are manually moved using a shovel.

Keywords: Expert system; Fuzzy; Pain ; Risk; Sand; Severity; Shoveling; Task

1. INTRODUCTION

Shoveling, a form of manual handling with the use of shovel, can be physically demanding to the cardiovascular system (heart and lungs), as well as bringing about muscle soreness, especially when done at fast rates. Improper techniques in shoveling can also cause severe back pain (Adeyemi et al., 2013: UV, 2011; CCOH, 1999). Cumulative trauma disorder and carpal tunnel syndrome are injuries that can occur from using shovel because shoveling requires wrist bending and gripping. Damage may occur between the finger tendons and the structure of the carpal tunnel due to tendon inflammation (Kroemer, 1989). Several studies have reported that soft tissue injuries are the most common among disorders caused by shovelling (Kaj, 2014;

*Corresponding author's email: adeyemi.hezekiah@oouagoiwoye.edu.ng, Tel. +234-8032161922
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Ryan et al., 2013; Véronique et al., 2004). Musculoskeletal disorders (MSDs) have been reported as one type of injury connected with the use of shovel. The study of MSDs and their connections with ergonomics illustrates that the "forceful use of shovels" and lifting heavy loads are leading causes of MSDs (Fathallah, 2010). It has also been advised that there is a need to take notice of any symptoms of repetitive strain and a need for awareness of any warning signs of cardiac distress—including shortness of breath, chest and/or upper body pain, palpitations, and other symptoms, such as anxiety, sudden extreme fatigue, nausea, or dizziness—as potential injuries from shovelling tasks (CPA, 2009).

Shovelling-related injuries send on more than 11,000 adults to hospital every year the average (Kelli, 2011). It was reported that U.S. hospitals treat an average of about 11,500 people a year whose injuries are related to shovelling snow. More than half of these injuries resulted from acute musculoskeletal exertion, while nearly 7% were related to cardiac problems, such as heart attack (Ann, 2011). Mikaela (2011) also reported that around 195,100 Americans were treated in emergency rooms for snow shovelling-related incidents from 1990 to 2006.

Shovelling-related Injuries among workers may lead to functional breakdown, increase hospital bills, and affect personal or national economic growth. Therefore, there is a need for a proactive and consistent approach to work-related risk assessment among this group of workers; according to the HSE, (2004), this should include the task, the load, the working environment, and individual capability. Examination of existing activities may also reveal opportunities for avoiding manual handling–related risk of injury, and the workplace layout can often be designed to minimize the transfer of materials. Some authors reported on assessment and/or management of risks in shovelling tasks (Anahad, 2011; Ann, 2011; Dhananjay & Mohammed, 2013; Jack, 2015; Bridger et al., 1998); however, using fuzzy logic for such efforts is very uncommon.

Fuzzy set theory (FST) is a proven technique for handling uncertainty connected with a task (Zadeh, 2006). It is a primary approach for representing pain (Araujo & Miyahira, 2011), but it is also frequently applied to risk assessment. Among many successful attempts, Adeyemi et al. (2015) used a fuzzy inference system to developed an expert system called Musculoskeletal Disorders–Risk Evaluation Expert System (MSDs-REES); this is capable of assessing risks associated with manual material handling. Moreover, Javad et al. (2015) used a fuzzy rule–based diagnostic system to detect lung cancer. Araujo and Miyahira, (2011) proposed a tridimensional fuzzy pain assessment for representing professional, social, and sexual factors related to the fifth vital sign of medical conditions. Furthermore, a Fuzzy Logic Expert System (FLES) was developed for lifting risk evaluation by Adeyemi et al. (2013).

A fuzzy system is a static nonlinear mapping between its inputs and outputs. A fuzzy set has values with partial membership along with the crisp values. Elements in a fuzzy set can overlap, so a given crisp value can belong to multiple fuzzy sets with different membership degrees in each set (Mayilvaganan, 2014). One of the basic principles of fuzzy logic is the degree of membership determined by "fuzzifying" each data point using the input fuzzy set. The input fuzzy set is determined by the system designer to break down the complete range of possible input values into membership functions (MFs). Each MF has a value of either 0 or 1 and a range specifying the minimum and maximum input values. Several shapes for the MF can be used, including trapezoidal, Gaussian, and triangular (Bansal, 2011).

The aim of this study was to develop a shovelling-related pain assessment tool that can be used as a computerized representation of human ergonomics expert assessment in the study domain. The objectives were to determine whether there is difference between the workers' self-reported risk scale values and/or interpretations and that predicted by the developed expert system.

2. MATERIALS AND METHODS

2.1. Task and Subject Selection

A worker participatory approach was used in this study. In total, 120 physically healthy male workers experienced in the use of a shovel for manual material movement from eight (8) sand mine locations in the south-western Nigeria volunteered to participate in the study. Consent of all potential volunteers was received orally after they were informed that their participation in the study was voluntary. The purpose of the study and the confidentiality of the information provided were emphasized.

2.2. Personal Data, Job Demand, and Work Station Assessment

Personal data were collected from participants using a well-structured questionnaire for parameters like age, years of working experience on the current job, and physical health conditions. The questions were structured in a simple way and interpreted to workers in their local languages. Using a modified version of Nordic Questionnaire as reported by Kuorinka et al. (1987), job-related discomfort in workers' different body regions in the past month were measured.

2.2.1. Assessment of shovelling task parameters

The study proposed an expert system to assess the shovelling-related pain risk. Four input variables were considered, representing potential risk factors in shovelling as highlighted by CCOHS (1999). The variable were scooping rate, scooping length, shovel load, and throw distance. The output variable, called the shovelling-related pain risk value, was determined by the fuzzy logic inference engine.

2.2.2. Work-related pain severity assessment

A numeric rating scale (NRS) tool was used for the assessment of pain intensity as felt by the workers while carrying out the shovelling task. The tool asked workers to rate how unpleasant the pain was by assigning a numerical value with value from zero (0), indicating no pain, to 10, representing the worst pain. The NRS is the most widely used pain intensity scale for adults and is sensitive to assessing acute pains (Breivik, 2000; Ellen, 2012).

2.2.3. Variable measurements for shovelling tasks

The rate of scooping sand by each subject was counted within a space of 1 minute using a stopwatch. Scooping total time before a break was measured using a stopwatch. Shovel mass plus load mass (Kg) was measured randomly four times for each subject using a digital weighing scale, and the average value was computed. Throwing distance (m) of the shovel load from the origin to the destination was measured using a meter rule. All measuring instruments were inspected before the commencement of measurement to ensure accuracy. All linear measurements were recorded to the nearest tenth of a centimeter. The tape rule used had a range of 150 cm and was made of latex material with calibrations in centimeters. Its flexibility allows it to be used for different measurements. The weighing scale, calibrated in kilograms, had a flat surface on which objects could be positioned. The capacity of the scale was 120 Kg. The digital stopwatch used simply measured and displayed the time interval from an arbitrary starting point that began at the instant the stopwatch was started. It measured the time interval using a frequency source.

2.3. Fuzzy Logic and Sand Shovelling Risk Evaluation

In this study, we used a trapezoidal membership function (TMF) to convert the crisp set into a fuzzy set. TMFs represent a more generalized form of MF and the most generic class of fuzzy numbers with a linear MF. Moreover, TMFs have greater applicability in modelling linear uncertainty in scientific and applied engineering problems (Bansal, 2011). The trapezoidal curve is a function of a vector, x, and depends on four scalar parameters, a, b, c, and d, as given by the following:

$$f(x;a,b,c,d)=\begin{cases} \frac{x-a}{b-a}, & a \le x \le b \\ 0, & x \le a \\ 1, & b \le x \le c \\ 0, & d \le x \\ \frac{d-x}{d-c}, & c \le x \le d \end{cases} \tag{1}$$

Or more compactly by:

$$F(x;a,b,c,d) = \max\left(\min\left(\frac{x-a}{b-a}, 1, \frac{d-x}{d-c}\right), 0\right) \tag{2}$$

The parameters *a* and *d* locate the "feet" of the trapezoid and the parameters *b* and *c* locate the "shoulders" (MathWorks, 2016).

2.4. Development of the Pain Intensity Prediction Expert System (PIPES)

Development of the fuzzy based PIPES comprised three steps, as follows: fuzzification of input task variables and output risk value, determination of the application rules and inference method, and defuzzification of the risk value (Smita, 2013).

2.4.1. Fuzzification of input task variables

Four major shovelling task risk factors, namely scooping rate, scooping time, shovel load, and throw distance were selected as input variables for the system. The choice of these variables was in accordance with the CCOHS (1999), which identified them among the prominent risk factors in manual material moving using a shovel, the guidelines of which are highlighted in Table 1. The system was developed from the knowledge of an expert, who detailed three (3) linguistic values for each of the input variables and four (4) linguistic values for the output variable. These were carefully derived using Table 1.

Table 1 Guidelines in shovelling to avoid fatigue and injury

Parameters	Optimal Condition
Rate	15 scoops per minute
Length of time	No longer than 15 minutes
Shovel load	Total weight should not exceed 5–7 Kg
Throw height	Should not exceed 1.3 m
Throwing distance	Around 1 m

Three linguistic values for the variable "Scooping Rate" were identified, as follows: lower than standard, normal standard, and above standard. Intervals for each of these linguistic values are given in Table 2.

Table 2 Fuzzy set of the "Scooping Rate" input variable

Linguistic Term	Interval
Lower than standard (LTS)	0, 0, 13, 14
Normal standard (NS)	13, 14, 15,16
Above standard (AS)	15,16, 20, 20

Three linguistic values for the variable "Scooping Time" were identified, as follows: shorter than normal, within normal range, and longer than normal. Intervals for each of these values are given in Table 3.

Table 3 Fuzzy set of "Scooping Time" input variable

Linguistic Term	Interval
Shorter than normal (STS)	0, 0, 13, 14
Within normal range (WNR)	13, 14, 15,16
Longer than normal (LTN)	15,16, 50, 50

Three linguistic values for the variable "Scooping Time" were identified, as follows: weight below recommended, recommended weight, and weight above recommended. Intervals for each of these values are given in Table 4.

Table 4 Fuzzy set of the "Shovel Load" input variable

Linguistic Term	Interval
Weight below recommended (WBR)	0, 0, 4, 5
Recommended weight (RW)	4, 5, 7, 8
Weight above recommended (WAR)	7, 8, 15,15

Three linguistic values for the variable "Scooping Time" were identified, as follows: shorter than approved, normal distance, and above approved distance. Intervals for each of these values are given in Table 5.

Table 5 Fuzzy set of the "Throw Distance" input variable

Linguistic Term	Interval
Shorter than approved (STA)	0, 0, 0.6, 0.8
Normal distance (ND)	0.6, 0.8, 1.0, 1.2
Above approved distance (AAD)	1.0, 1.2, 4, 4

Four linguistic values for the output variable "Shovelling-related Pain (SRP) Risks" were identified, as follows: no pain, mild pain, moderate pain and severe pain. Intervals for each of these values are given in Table 6.

Table 6 Fuzzy set of the "Shovelling-related Pain Risks (SRPR)" output variable

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

2.4.2. Determination of application rules and inference method

With the four inputs and three linguistic values each, there are (3^4) 81 rules (all possible combinations of the premise linguistic values) fired into the inference engine for the expert system. Fuzzy rule and fuzzy reasoning are the most important modelling tools based on FST. They are considered the backbone of fuzzy inference systems (Jang, 1996).

Some of the rules are as follows:

- *Rule 1. If (ScoopingRate is LTS) and (ScoopingTime is STS) and (ShovelLoad is WBR) and (ThrowDistance is STA) then (SRP-Risk is NP)*
- *Rule 5. If (ScoopingRate is LTS) and (ScoopingTime is WNR) and (ShovelLoad is RW) and (ThrowDistance is STA) then (SRP-Risk is MP)*

- *Rule 10. If (ScoopingRate is LTS) and (ScoopingTime is STS) and (ShovelLoad is WBR) and (ThrowDistance is ND) then (SRP-Risk is MP)*
- *Rule 17. If (ScoopingRate is LTS) and (ScoopingTime is LTN) and (ShovelLoad is RW) and (ThrowDistance is ND) then (SRP-Risk is MRP)*
- *Rule 18. If (ScoopingRate is LTS) and (ScoopingTime is LTN) and (ShovelLoad is WAR) and (ThrowDistance is ND) then (SRP-Risk is MRP)*
- *Rule 26. If (ScoopingRate is LTS) and (ScoopingTime is LTN) and (ShovelLoad is RW) and (ThrowDistance is AAD) then (SRP-Risk is MRP)*
- *Rule 27. If (ScoopingRate is LTS) and (ScoopingTime is LTN) and (ShovelLoad is WAR) and (ThrowDistance is AAD) then (SRP-Risk is SP)*
- *Rule 35. If (ScoopingRate is NS) and (ScoopingTime is LTN) and (ShovelLoad is RW) and (ThrowDistance is STA) then (SRP-Risk is MRP)*
- *Rule 45. If (ScoopingRate is NS) and (ScoopingTime is LTN) and (ShovelLoad is WAR) and (ThrowDistance is ND) then (SRP-Risk is SP)*
- *Rule 81. If (ScoopingRate is AS) and (ScoopingTime is LTN) and (ShovelLoad is WAR) and (ThrowDistance is AAD) then (SRP-Risk is SP)*

2.4.3. Defuzzification of risk value

The SRP risk as a consequence of the system was determined by inference of the fuzzy rule set using Mamdani's inference and centroid defuzzification of the fuzzy output. Defuzzification is the inverse process of fuzzification. It involves combining the fuzzy outputs of all of the rules to give one crisp value. Thus, the crisp value output is given by the defuzzification process after estimating its input value (Monish, 2015). Mamdani's method is the most commonly employed fuzzy methodology. The technique is intuitive, has widespread acceptance, and is well suited to human input (Sumathi, 2010). The centroid defuzzification method is also a commonly used technique, and it has been proved to be extremely accurate (Yen, 1999).

2.5. Data Analysis and PIPES Validation

Statistical Package for the Social Sciences (SPSS) Version 16.0 (SPSS, 2007) was used to analyze the collected data. To test the quality of PIPES, samples from the recorded variables were selected and run in the developed expert system. The outcomes of the values were interpreted based on an expert's rating. The PIPES-generated numeric values were compared with the workers' self-reported pain (WSRP) NRS for correlation strength. Spearman's rho was used for significance tests of correlation coefficients at a *p*-value of 0.01. According to Gerstman (2006), correlation quantifies the extent to which two quantitative variables go together. Correlation strengths can be classified as weak, $0 < |r| < 0.3$; moderate, $0.3 < |r| < 0.7$; and strong, $|r| > 0.7$. Garcia (2011) stated that instead of relying on correlation scales alone, other statistics can also be used for further confirmation. Hence, the independent sample t-test was used to analyze the means of the unrelated groups at $p < 0.05$. According to Pagano (2004), the independent samples t-test evaluates the difference between the means of two independent groups. It appraises whether the means for two independent groups are significantly different from each other. The independent sample t-test is probably the single most widely used test in statistics (Matthew, 2004).

3. RESULTS

The expert system, PIPES, used fuzzy logic that was implemented in Matlab 7.8 using values of the input variables scooping rate, scooping time, shovel load and throw distance to obtain the results of the mapping of the system with pain severity risk (PSR) as the output. The algorithm of the inference engine applied 81 sets of linguistic rules to generate the output variable as a crisp value.

Figures 1–5 show the MF graphs, which display all of the MFs associated with all of the input and output variables for the entire fuzzy based model inference system as presented by MATLAB.

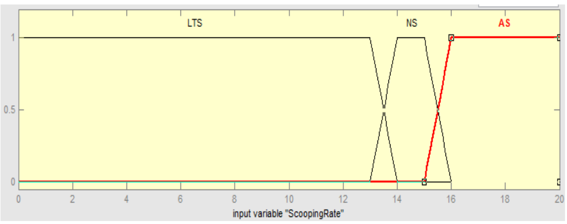

Figure 1 Membership function for the input variable "Scooping Rate"

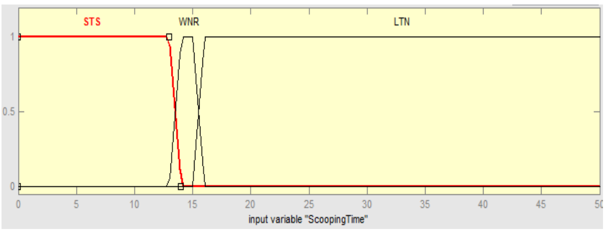

Figure 2 Membership function for the input variable "Scooping Time"

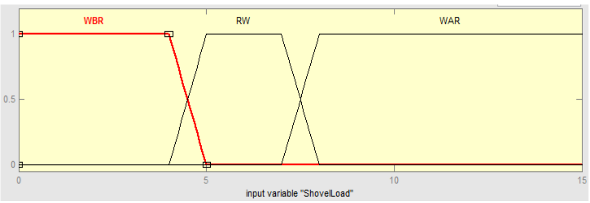

Figure 3 Membership function for the input variable "Shovel Load"

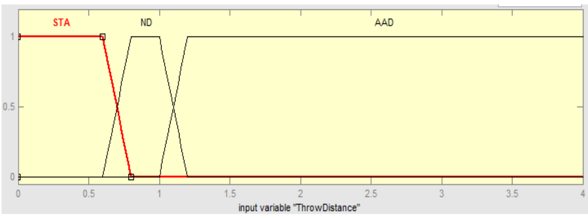

Figure 4 Membership function for the input variable "Throw Distance"

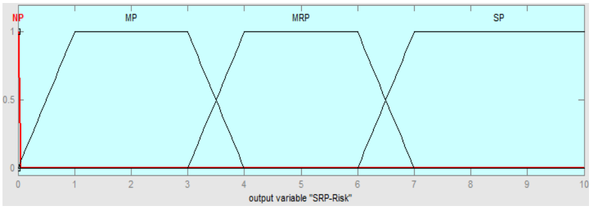

Figure 5 Membership function for the output variable "Shoveling-related Pain"

Figure 6 shows the output of graphical rule editor interface after the construction of 81 linguistic rule statements based on the descriptions of the input and output variables.

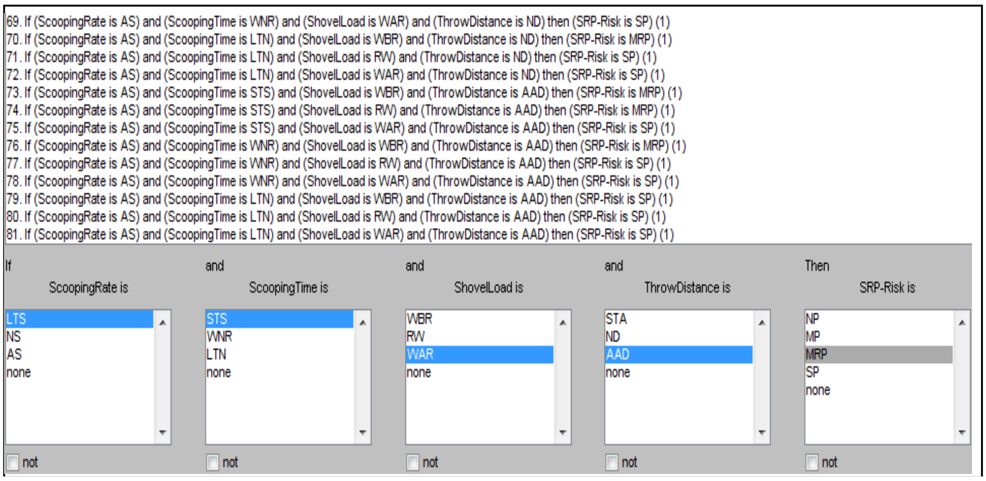

Figure 6 The graphical rule editor interface

Considering a scenario of a subject with the measured task variables of ScoopingRate = 8, ScoopingTime = 33 min, ShovelLoad = 7.5 kg, and ThrowDistance = 1.2 m, from Figure 1, the input membership function (IMF) for the variable "Scooping Rate" is 1.0 (LTS) (μ_{LTS}(ScoopRate)=1.0). From Figure 2, the IMF for the variable "Scooping Time" is 1.0 LTN (μ_{LTN}(ScoopingTime)=1.0). From Figure 3, the IMF for the variable "Shovel Load" is 0.5 (RW) (μRW(ShovelLoad)=0.5) and 0.5 (WAR) (μ_{WAR}(ShovelLoad)=0.5). Finally, from Figure 4, the IMF for the variable "Throw Distance" is 1.0 (AAD) (μ_{AAD}(ThrowDistance)=1.0) and 0.0 (ND) (μ_{ND} (ThrowDistance)=0.0). Combining the rules, the following logical implication statements are applicable:

Rule 18. If (ScoopingRate is LTS) and (ScoopingTime is LTN) and (ShovelLoad is WAR) and (ThrowDistance is ND) then (SRP-Risk is MRP)

Rule 26. If (ScoopingRate is LTS) and (ScoopingTime is LTN) and (ShovelLoad is RW) and (ThrowDistance is AAD) then (SRP-Risk is MRP)

Rule 27. If (ScoopingRate is LTS) and (ScoopingTime is LTN) and (ShovelLoad is WAR) and (ThrowDistance is AAD) then (SRP-Risk is SP)

Each of the rules was first quantified with fuzzy logic to perform inference by quantifying the meaning of the premises of the rules. To determine the applicability of each rule (matching), the inference mechanism identified which rules are ON (i.e., if its premises MF) $\mu_{premise}$[ScoopingRate, ScoopingTime, ShovelLoad, ThrowDistance] > 0. The inference engine combined the recommendations of all the rules to come up with a single conclusion. The final stage was defuzzification, which operated on the implied fuzzy set (output fuzzy set) produced by the inference mechanism and combined the effects to provide the "most certain" risk output, as shown in the rule viewer (Figure 7). The rule viewer displays a roadmap of the whole fuzzy inference process. The first four left plots across the top of the figure represent the antecedents, and the fifth represents the consequence of the first rule. Each rule is a row of plots, and each column is a variable. After the user manually specifies the four input values, a new calculation is performed, and the user can see the whole fuzzy inference process take place. The rule viewer allows the user to interpret the entire fuzzy inference process at once.

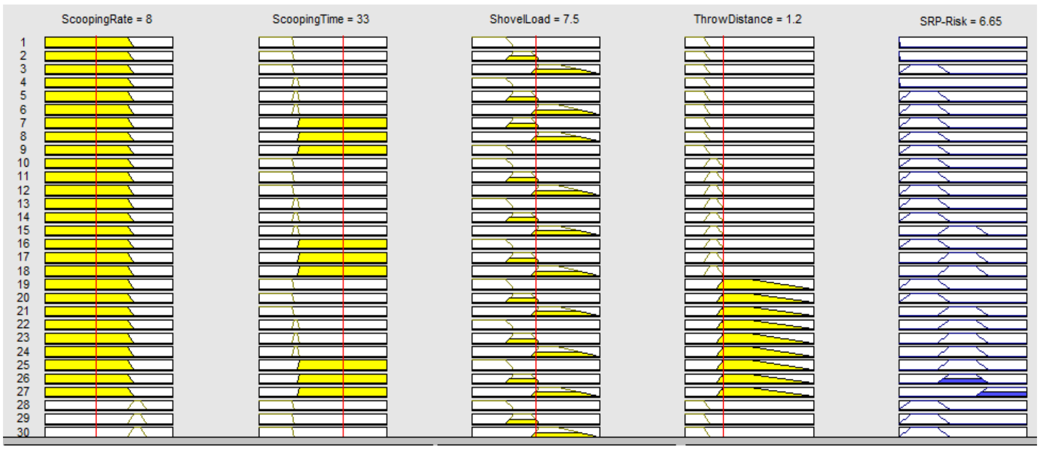

Figure 7 Rule viewer of the whole fuzzy inference process

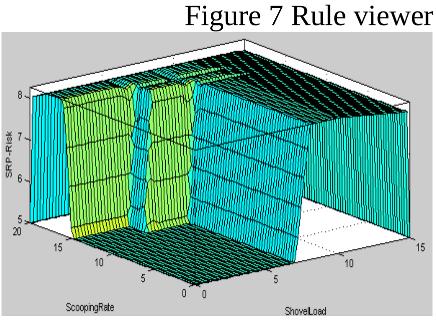

Figure 8 Surface found by mapping of the fuzzy

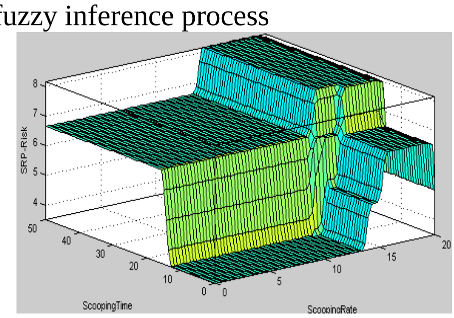

Figure 9 Surface found by mapping of the fuzzy

model ("Scooping Rate" and "Shovel Load" variables)

model ("Scooping Time" and "Shovel Rate" variables)

The surface viewer shows how the system varies over the ranges of variables (Figures 8 and 9). It can be noted in Figure 8 that when the shovel load is below 6 kg and the scooping rate is below 15, the pain risk is around 5, representing "moderate pain." Moreover, Figure 9 illustrates that when the scooping time is around 10 minutes and the scooping rate is around 12, the risk is "mild." However, whenever any of the antecedent variables increases above these values, the risk is also expected to increase.

3.1. Model Validation

Table 7 presents data on 20 selected workers with ≥ 2 years of working experience on the current job, including their corresponding measured shovelling task variables, the WSRP NRS, the PIPES NRS, and interpretations of the numeric ratings. While the highest and lowest recorded values of scooping rate among the selected subjects were 18 and 4, respectively, those of scooping time were 33 and 8 min. Ten kilograms and 5 kg were the highest and lowest shovel loads recorded among the group, respectively, while the lowest throw distance was 0.9 m. On average, the WSRP NRS value was 4.35 ± 2.1 and that of PIPES was 4.75 ± 2.2.

Table 7 Task variables measured, WSRP NRS, and PIPES predicted NRS for 20 out of 120 evaluated workers in the sand shovelling task

Sample	Scooping Rate (No.)	Scooping Time (min.)	Shovel Load (Kg)	Throw Dist. (m)	WSRP NRS	Affected workers Rating	PIPES NRS	Model Rating
1	5	32	8	2	6	Moderate	8.26	Severe
2	7	28	6	1.4	6	Moderate	5	Moderate
3	11	15	5.5	1.1	4	Moderate	3.5	Moderate
4	6	12	5	1.2	3	Mild	2	Mild
5	5	8	5	1.5	2	Mild	2	Mild
6	14	18	6	1	7	Severe	5	Moderate
7	8	23	7	2.2	2	Mild	5	Moderate
8	13	16	8	1.8	4	Moderate	8.26	Severe
9	9	14	7	1.3	3	Mild	5	Moderate
10	13	13	6	1.2	5	Moderate	3.5	Moderate
11	16	17	9	1.2	6	Moderate	5	Moderate
12	8	33	7.5	1.2	4	Moderate	6.65	Severe
13	16	16	9	1.7	9	Severe	8.26	Severe
14	8	10	8	1.1	3	Mild	3.5	Moderate
15	10	8	10	2.1	6	Moderate	5	Moderate
16	5	19	6.5	1.0	4	Moderate	5	Moderate
17	9	13	7.5	0.9	1	Mild	2	Mild
18	4	13	6	1.3	2	Mild	2	Mild
19	9	13	8	1	3	Mild	2	Mild
20	18	15.5	9	2.2	7	Severe	8.15	Severe
Average					4.35±2.1		4.75±2.2	

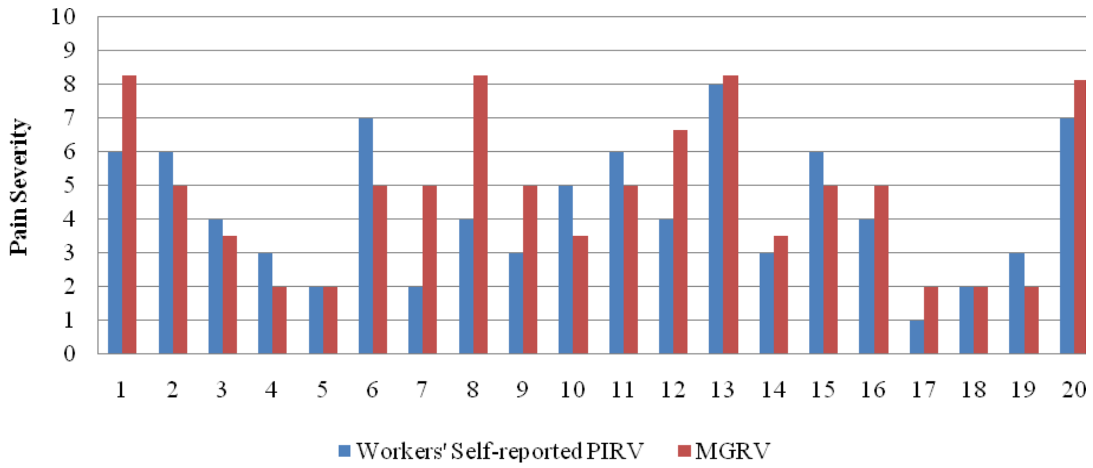

Figure 7 Comparison of the WSRP NRS and the PIPES suggested NRS

Figure 7 shows the individual data of the WSRP NRS and the PIPES-generated NRS. In all the divergences notable, 9 (45%) values of NRS for PIPES were higher than those of WSRP. However 33.3% in this category (samples 16, 17, and 20) had the same interpretations of "moderate," "mild," and "severe," respectively, for both WSRP and PIPES. In a similar trend, 45% of the divergences had NRS values of PIPES lower than those of WSRP. However, only sample 6, representing 11.1% in this category had a rating of WSRP (severe) that differed from that of PIPES (moderate). All others had the same rating. Meanwhile, two samples, 5 and 18—representing 10% of the total—had the same NRS values with the same interpretations.

3.1.1. Correlation test between WSRP and PIPES

After comparing the result of NRS generated by PIPES with that of WSRP for correlation strength using Spearman's rho, a significant correlation was found r = 0.70, p<.01. The coefficient of determination of 0.7 suggests 70% variability.

3.1.2. Independent samples t-test between WSRP and PIPES

The t-test to determine the mean difference between NRS of WSRP and PIPES found that WSRP showed a statistically significantly lower level of risk (4.35 ± 2.1) compared to PIPES (4.75 ± 2.2), $t(38) = -0.591$, $p = 0.558$. However, the groups' means were not significantly different, because the value of "Sig. (2-tailed)" was greater than 0.05.

4. DISCUSSION

According to Ellen (2012), pain injuries among workers have been associated with functional impairment, increased healthcare utilization and costs, and so on. According to Breivik et al. (2008), adequate assessment of pain is an essential prerequisite of successful pain management; when there is inadequate pain assessment, there will be resultant failings in management. In an effort to improve the detection and management of pain, a proactive, consistent approach is necessary to screen for pain and assess workers for work-related injuries. PIPES was proposed in this study for the detection and/or management of pain in shovelling-related tasks. The expert system was tested with sets of shovelling task variables. Comparisons between WSRP NRS and PIPES NRS were carried out to evaluate the performance of the expert system. It was found that 65% of all ratings/interpretations of risk values by PIPES and WSRP were the same, while 30% of PIPES predictions were higher in severity than the values measured using WSRP. However, it is better not to underrate the risk involved in the task in this context, as this may be safer for many workers. Underrating the task risk may expose workers to higher levels of injuries.

There were some notable variations in the NRS interpretations. For instance, the WSRP interpretation for case 7 was “mild,” while PIPES predicted the next level of risk intensity of “moderate”. In addition, for case 8, PIPES predicted “severe pain,” while WSRP showed immediate lower risk intensity of “moderate” pain. The ratings and interpretations of case 5 and case 18 corresponded, as the worker was assessed as being under “mild risk” in performing the manual task.

The use of expert systems in assessment of risk and/or pain in hand-intensive work is common. However, similar studies using this approach are rare. PIPES is an ergonomic tool capable of reducing work-related injuries among the group of workers in the application area. The task method and/or workplace can be redesigned based on the effects of each input variable, thereby reducing the continual exposure of workers to one or more risk factors. According to OSHA (2000), such factors may initially cause pain in some regions of the body and over time result into MSDs, which are injuries to the muscles, tendons, nerves, ligaments, joints, and blood vessels. MSDs are reported to be the major cause of work disability in manual material handling (Tom, 2012); they may affect the back, shoulder, elbow, wrist, or hand regions of the workers.

The results of the PIPES NRS predictions were statistically significant compared to workers’ reported situations for the same input values. The results obtained from the comparison were satisfactory, as the correlation strength was strong, and the t-test for means was not significantly different. The few weaknesses recorded for PIPES may be due to issues in the dataset, which tends to reduce the accuracy of the predictions, especially in case 6 where the expert system prediction was lower than the worker’s reported pain severity.

There are uncertainties in the performance of shovelling tasks. There are different parameter combinations for different workers. This uncertainty, imprecision, and subjectivity in the data and in the evaluation process can be handled by a fuzzy logic approach, as reported previously (Zadeh, 2006). The MF can be tailored to the worker. Considering the classification of a throw distance of 1.0 m, for instance, this value fits into “normal distance” (ND), while 1.5 m fits into “above approved distance” (AAD) with a membership degree of 1.0. The fuzzy approach considered the inherent uncertainties of the classification process, such as in the case of 1.1 m, which simultaneously fit into ND and AAD with some membership degrees. However, the parameter combinations cannot be varied and broadened for each user separately. Thus, the system is not flexible enough.

PIPES can find applications in the construction industries, sand mine locations, and any workplaces where materials are manually moved by shovel. The expert system can be used as a computerized representation of ergonomics expert reviews in the application area. However, in future efforts, the inclusion of more variables like posture, shovel design, and other related risk factors can be considered for improvement of the model.

5. CONCLUSION

This study proposed PIPES for the detection of pain degree in shovelling-related tasks. Arising from the findings, the Spearman’s rho correlation coefficient between the WSRP and PIPES NRS was found to be 0.70, which is a strong result. WSRP had a statistically significantly lower level of NRS risk (4.4 ± 2.1) compared to that of PIPES (4.8 ± 2.2), $t(38) = -0.591$, $p = 0.558$. However, the groups’ means were not significantly different. Sixty-five percent of all NRS interpretations were the same for both WSRP and PIPES, while for 83% of the remaining interpretations, the NRS predictions by PIPES were higher in severity than those of the WSRP. PIPES can be applied in the construction industries, sand mine locations, and any workplaces where materials are manually moved using a shovel. The expert system can be employed as a computerized representation of human ergonomics expert assessments in these application domains.

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