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A LOGISTIC REGRESSION MODEL TO PREDICT INCIDENT SEVERITY USING THE HUMAN FACTORS ANALYSIS AND CLASSIFICATION SYSTEM

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A LOGISTIC REGRESSION MODEL TO PREDICT INCIDENT SEVERITY USING THE HUMAN FACTORS ANALYSIS AND CLASSIFICATION SYSTEM

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ABSTRACT

The Human Factors Analysis and Classification System (HFACS) is a framework based on Reason's "Swiss Cheese Theory" and is used to help identify causal factors that lead to human error. The framework has been used in a variety of industries to identify leading contributing factors of unsafe events, such as accidents, incidents and near misses. While traditional application of the HFACS framework to safety outcomes has allowed evaluators to identify leading causal issues based on frequency, little has been done to gain a more comprehensive view of the system's total risk. This work utilizes the concept of event severity along with the HFACS framework to help better identify target areas for intervention among unsafe events in wind turbine maintenance.

The objective of this work was to determine if there are any relationships between the certain HFACS causal factors and an incident's severity. The analysis was based on 405 cases which were coded for contributing factors using HFACS and were rated for actual and potential severity using a 10-point severity scale. Models for predicting potential and actual severity were generated using logistic regression. These models were then validated using actual data. Although the findings were not significant, it was determined that decision errors and preconditions to unsafe acts: technological environment were major contributors to events with high potential severity.

One limitation of this work was the limited availability of complete data on which to conduct the analysis. So, while the analysis produced non-significance, it is anticipated that as more data becomes available, the models will yield more concrete findings. Regardless, understanding the relationships among incident causal factors and outcomes

may shed light on those causal factors which have the potential to lead to catastrophic events and those which may lead to less severe events.

DEDICATION

I dedicate this thesis to my family.

ACKNOWLEDGMENTS

I would like to thank Dr. Gramopadhye for presenting me with this opportunity. I would also like to thank Dr. Shappell and Dr. Stringfellow for their constant support and guidance.

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CHAPTER ONE

INTRODUCTION

Whether determining which stock to sell to achieve the greatest financial reward or deciding where to focus this year's budget for the purchase of safety equipment for your workforce, Risk Management (RM) is a practice adopted by many both formally and informally. With regards to industrial safety, RM is a refined discipline and generally considers the identification, assessment and prioritization of hazards and their consequences in an effort to strategically and effectively minimize the risk through the introduction of certain interventions. As such, effective RM does not just address the resulting outcome, like number of lacerations among a given population, but rather aims to address the "root cause(s)" which ultimately contributed to the outcome.

One way of helping to identify the "root causes" or contributing causal factors of an unsafe event is by using the Human Factors Analysis and Classification System (HFACS). This framework has been used successfully by a number of industries to identify common latent causal factors in the organizations' safety performance. Most often, incident and accident cases are reviewed and classified using the HFACS framework only to generate an overall list of the most frequently occurring causal factors (both active and latent). While targeting interventions toward these high-frequency causal factors may prove effective, using this method there is no way to distinguish between the magnitude of each event. For instance, the highest occurring causal factor may be a skill-based error in the form of slips, trips, or falls. As a result, resources may be diverted and allocated to addressing this single issue. However, further analysis reveals that the severity or consequences of these slips, trips, or falls are minimal and are only resulting in minor scrapes and bruises. Meanwhile, other less frequent but more catastrophic events go un-noticed simply due to the low frequency of occurrence. This example highlights the need to incorporate another parameter, incident severity, into the evaluation process which will 1) provide a more detailed picture of safety performance in an organization and 2) enable managers to better identify target areas for intervention.

It is anticipated that certain levels of incident severity are generally influenced by a common set of similar active and latent causal factors (according to the HFACS framework). The question becomes, what causal factors are common to high-severity incidents, medium-severity incidents, and low-severity incidents? And, can we predict the severity of an incident given an existing set of causal factors?

1.1 Objective

The objective of this thesis is to develop a predictive model for determining the actual and potential severity of a future incident as a function of existing HFACS causal factors.

1.2 Motivation

This model should be developed for the following reasons:

1) Future high severity accidents can be prevented by identifying and fixing root causes.

2) A standard methodology can be developed which fully utilizes the potential of HFACS in order to develop probabilistic models. In the literature so far, this approach has not been taken.

3) Management decisions can be aided by determining the causal categories which attribute to an increase in probability of high severity. Efforts can thus be directed towards fixing causes which result in higher severity incidents. Having statistically significant causal factors makes decision makers trust the means to fix them.

4) The overlooked near accident cases can be fully utilized. Most incident reports have higher proportion of near accident cases than actual accidents. Authors so far have only considered actual severity for developing prediction models, which is based on accidents. Also, there have not been any established procedures that help rate potential severity. A basic framework for rating potential severity will be established.

1.3 Thesis Layout

The first chapter will begin with some basic definitions and terminologies. This will be followed by a discussion on the topic of risk and risk assessment. The theory of human error will be discussed briefly. There will be discussions on the topic of severity. Then, the Human Factors Analysis and Classification System (HFACS) will be reviewed. These will be the human factors components used in this study. Mathematical tools have been used for determining the relationship between causal factors and incident severity in this study. Hence, logistic regression techniques and the various terminologies associated with them will be discussed in chapter three.

The methodology that will be used for this study will be discussed in detail in the next chapter. The methodology section will include all the stages in which this study was conducted, with details of each. The last chapter is results and conclusion, where the results of this study will be presented. Also, limitations of this study and future research will be discussed.

CHAPTER TWO

BACKGROUND

In this chapter, some basic definitions and terminologies related to accident investigation and safety engineering will be discussed.

2.1 Basic Definitions

In his work for measuring accident severity, Davidson (2004) has compiled the following definitions of important terms in safety:

Accident: “An undesired event that results in harm to people, damage to property or loss to process. It is usually the result of a contact with a substance or a source of energy above the threshold limit of the body or structure.”(Bird & Germain, 1989, p.36)

Near accident: “An event which, under slightly different circumstances would have resulted in harm to people, damage to property, or loss to process.” (Bird & Germain, 1989, p.36)

Incident: An incident comprises of an accident or a near accident. “In a broader loss control definition, it refers to an event which could or does result in a loss.” (Bird & Germain, 1989, p.36)

2.2 What is a risk?

The classical definition is that risk (for example, of an accident) is the product of the probability of that event and (a unified measure of) the (assumed negative) consequences that necessarily accompany that event (Sheridan, 2008). Other definitions of risk state that, risk is the probability or likelihood of an injury or death (Christensen, 1987). The notion of risk involves both uncertainty and some kind of loss or damage that might be received (Kaplan & Garrick, 1981). All these definitions formulate risk as product of probability and consequence or severity. Sheridan (2008) argues that, risk *R* with the following formula:

$$R = P_E \times \sum_i (P_i | E \times C_i).$$

In this case, P_E is the event probability and the remaining term explains the consequences of all events that could occur, given that the initial event occurs. Here, C_i is the consequence.

For an incident E to occur, three other probabilities are taken into account. The first is the probability of opportunity or exposure to a hazard. The second is attributed to human error, and takes into account the probability of this error to occur when presented with the opportunity or exposure. Lastly there is the probability that there is no recovery to favorable conditions, given the error occurs. Hence, the probability of this unfavorable outcome is the product of the three probabilities (Sheridan, 2008):

$$\begin{aligned} &P(consequence) \\ &\quad = P(opportunity) \times P(error|opportunity) \\ &\quad \times P(no\ recovery\ in\ time|error) \end{aligned}$$

The term $P(consequence)$ is the term P_E used earlier in the definition of risk. This equation explains the importance of the opportunity or exposure, for an unfavorable outcome to occur.

In the equation for risk R, the term C_i is consequence or severity. There is a difference between the terms risk, hazard, and uncertainty. As already stated, uncertainty and damage constitute risk, and uncertainty is just the probability that the desired event may not occur as planned. Hazard is a source of danger, while risk is the possibility of loss or injury. Kaplan and Garrick (1981) further theorized a relationship between a risk and a hazard:

$$Risk = Hazard \div Safeguards.$$

This equation states that risk is a ratio of hazards and safeguards. There is always a small chance of a desired event or activity to have an unfavorable outcome. Thus, risk can be reduced to an infinitesimal value by increasing safeguards, but never brought down to zero, because a hazard always exists.

Risk analysis answers the following questions: What can happen? How likely is it to happen? If it occurs, what are the consequences (Bedford & Cooke, 2001)? The basic method of risk analysis is the identification and quantification of scenarios, occurrence probabilities and consequences. Risk, from the context of industrial safety, can be viewed as a set of scenarios, each with a specific probability of occurrence and quantifiable impact of consequences (Kaplan & Garrick, 1981). The emphasis here is to model a specific system (wind turbine maintenance) and construct a mathematical model that links the accident causation factors and the accident severity. In order to achieve this, it is important to quantify accident severity.

2.3 Techniques for risk assessment

The method to measure risk and categorize risk involves the use of certain 'first-order' approaches (Glendon, Clarke, & McKenna, 2006). These are technical, economic, cultural and psychometric approaches. The technical approach considers risk as being primarily about seeking safety benefits in such a way that, the acceptable risk decisions are a matter of correct engineering. In this approach, science is given prime importance in investigating, analyzing and implementing safety and risk issues. Examples of this approach include Management Oversight and Risk Tree (MORT) and Failure Modes and Effects Analysis (FMEA). MORT is fundamentally similar to an event tree. On the other hand, the economic approach considers the expected benefit, rather than the harm caused, as the main factor for managing risk. The economic approach considers hazards as market externalities requiring intervention and social, cultural, political and anthropological notions are ignored (Viscusi, 1983). Cost-Benefit Analysis (CBA) is an example of the economic approach.

Cultural theory approach utilizes an anthropological framework for determining how groups in society interpret hazards and embed trust or distrust in institutions that create or regulate risk (Douglas, 1992). This is not a quantifiable approach, since it does not help predict how individuals will behave in their group, which might lead to hazards. The psychometric approach is based on Risk Perception (RP). RP is considered as a subjective phenomenon. This approach explains why people perceive hazards differently. This approach is considered to be the most influential model in the field of risk analysis by Siegrist, Keller and Kiers (2005). In this study, 26 potential hazards were asked to be rated not only in terms of severity, also personal factors such as scientific knowledge of the hazard, dread potential, newness and perceived immediacy of effect. This study aimed to establish that individual perception of a hazard is also an important criterion in categorizing risk, along with severity and frequency. However, it is difficult to obtain data regarding the perception that an employee might have about a hazard before an incident occurs. The data used in our study is compiled from an incident report, and each and every employee involved in the incident will have to fill in a questionnaire regarding their perception of the hazard on the basis of the factors described in the study discussed above. There are various approaches to measure and assess risk. Now, some techniques for applying these approaches into practice will be discussed.

A risk matrix is a table where columns are represented by probability of an event, frequency or its likelihood of occurrence, and rows represent an event's severity, impact or consequences. Risk is then determined as the product of probability and severity. Risk is not a measured attribute, but is derived from frequency and severity inputs through *a priori* specified formulas such as $Risk = Frequency\ X\ Severity$ (Cox, 2008). Risk matrices provide a clear framework for analyzing risks. They are easy to construct and understand. Also, they can easily accommodate for changes to the grid based on specific applications. On the other hand, it has been argued that, the construction and use of risk matrices does not need special expertise in the field of risk assessment.

Failure Modes and Effects Analysis (FMEA) is a technique which considers all the ways by which a system could fail and the consequences that could occur with each case. Root-cause analysis is used to identify the most responsible cause of the incident under question. State transition diagrams describe a system as it moves from one state to another, and limits the system to only one state at a time. An event tree describes the transition of the system from an initiating event to subsequent events. There is a probability associated with each subsequent event occurring after this initiating event. According to first order classification by Glendon, Clarke, and McKenna (2006), these techniques fall into the technical approach. The focus in this study is not only to review the concept of risk, but also to explore and experiment with the concept of severity. This study will utilize the technical and the risk perception approaches for developing a mathematical relationship between causal factors and incident severity.

2.4 Severity and the technical approach

Every occupational accident has a severity associated with it. The severity may be rated according to damage to an employee's health, or by cost incurred to the organization. The severity ratings developed so far take into consideration both these perspectives.

There are risk matrices which categorize risk according to frequency of an event and the impact of the event, as argued earlier. Such matrices indicate event probability on one axis and impact or severity on the other, their product categorizing an event of having higher risk based on higher impact and probability (Federal Aviation Administration, 2007). Some authors argue that these matrices have poor resolution; typical risk matrices can correctly and unambiguously compare only less than 10% of randomly selected pairs of hazards (Cox, 2008). The accuracy in quantifying actual risk is low for risk matrices, and should be used as an alternative to purely making random decisions. In the risk matrix technique discussed above, the probability of a particular event can be determined quantitatively based on frequency of the event. Consequence or severity, for example, has been 'given' values between 0 and 1 in the study by Cox (2008). This largely depends on the analyst's perception of the impact of the incident. This is where the risk perception theory comes into play.

Earlier, we discussed FMEA as a technique to analyze risk. FMEA considers the system in a binary state: pass or fail. It does not consider intermediate degrees by which a system is damaged, but rather the series of events that lead the system to failure. FMEA helps investigate all the events leading to a failure, but does not consider how each event leading to failure is affecting the system in terms of severity. FMEA hence does not register severity on a continuous basis, but rather on a binary basis.

A state transition probability diagram consists of a large possibility of conditions that the state of a system can be over time. A state transition diagram also does not incorporate severity of an incident. Hence, to include severity into these diagrams, one will have to imagine large number of states emerging from the current, each having a different severity rating. For example, a system can transition from state A to B with probability P_{AB}. This new state has a severity *s*. *S* can take on a large set of values, and hence there are a large number of states B with varying values of severity *s*. Hence, arguably, state transition probability diagrams can more accurately identify the risk of potential incidences than the FMEA technique. The same argument can be made for event trees. Event trees are used primarily, to determine the root cause of an incident, rather than help determine scenarios with varying severity. In the work by Ross (1981), a serious injury fault tree has been constructed to trace the path of events that lead to a serious injury. This is like an event tree, but focusing on only serious injuries. Ross retraces the path of a serious injury from the time of occurrence backwards. He concludes that a designated activity occurs with inadequate operator actions and unfavorable energy flow. The above technical approaches help analyze and classify the causes of incidents and their severity.

Currently, researchers have developed several probabilistic models to predict severity, given the potential causal factors. This approach for predicting the severity is based on the variables involved and a probabilistic model is developed. Li and Bai (2008) have developed a severity predicting model for motorcycle accidents. They propose a Crash Severity Index (CSI), which is the likelihood that a fatality will occur given a severe crash occurs. This index can take values between 0 and 1, and is determined statistically from the work zone variables. The closer the number is to 1, the higher the possible severity of injury. In a similar study by Dissanayake and Lu (2002) probabilistic models have been used to predict severity. Automobile crash severity in this study, has been categorized into five levels: No injury, possible Injury, non-incapacitating injury, incapacitating injury and fatal injury. The models developed calculate the probability of occurrence of an injury with a particular level of severity. This can be better formulated as: Probability [An incident that occurs has a particular severity level]. For example, a model has been developed in this study to calculate the probability of an incapacitating injury to occur. These models calculate the probability that a higher severity incident occurs, given that a lesser severity incident has occurred. For example, if a motorcyclist suffers a serious injury, what is the probability that the injury will be fatal?

2.5 Severity Scales

Lin, Hwang, and Kuo (2008) have reviewed various medical severity scales. The Injury Severity Scale (ISS) and the Abbreviated Injury Scale (AIS) are used by healthcare professionals to categorize the trauma faced by their patients (Copes, Sacco, Champion, & Bain, 1989). The most common scale is the ISS. AIS uses nine body regions to better summarize injury severity caused by multiple injuries. The ISS uses only six body regions, instead of nine (Baker, O'Neill, Haddon, & Long, 1974). The ISS scores are based on the sum of squares of the highest AIS scores for the top three most severely hurt body parts. The ISS scores range from 1 to 75. New Injury Severity Score (NISS) uses three most severe injuries independent of whether all three occur in the same region, to compute the sum of squares (Osler, Baker, & Long, 1997). These scales, however, lack the sensitivity to accurately classify less severe injuries (Lin, Hwang, & Kuo, 2008). Based on the part of the body injured and type of injury, physicians can accurately quantify trauma. Trauma for physicians is analogous to severity for safety engineers.

When considering a severity scale, management is interested in determining how the severity of the injury will impact the company financially. This may be a combination of production time lost, worker compensation claims, and equipment damaged. This is the reason why scales which classify only worker injury trauma; such as an AIS or ISS cannot be directly used to reflect cost to management.

A major power generation company has a severity scale which considers injuries based on workdays lost. This is 10 point scale with severity increasing from 1 to 10. The number of workdays lost has been estimated for each serious severity rating. Critical severity ratings 8, 9 and 10 represent permanent disability, fatality and multiple fatalities, respectively. Further, two types of severities have been used: potential and actual.

Based on the seriousness of the injury, the incident may result in significant financial loss to an organization. Many examples of the magnitude of financial loss have been reviewed by Asfahl (2005). In one example, the average total cost per worker fatality has been estimated as $790,000 (National Safety Council, 1996). The cost to the U.S.A.F. for a worker fatality has been estimated as $1,100,000 (U.S. Air Force, 1995). The costs mentioned above include the compensation, equipment and investigation costs. The U.S. Department of Energy estimates a loss of $1 million per employee fatality (Briscoe, 1982). Reportable injuries cost, on an average, $2000 per incident, while a cost of $1000 per day lost also has been estimated (Crites, 1995). The estimation of these costs comes from the legal and financial paradigm of safety based on the severity of the incident (Asfahl, 2005). Hence, the degree by which severity increases according to financial loss depends on the injury sustained. Severity scales should show the types of injuries, equipment damaged and the corresponding financial loss.

Sensitivity of a severity scale depends upon the application for which it is to be used. A mining environment, for example, will employ a ten-point scale for the variety of medium and serious injuries such as bruises, amputations and electrical shocks. On the other hand, a severity scale used for assessing injury to computer programmers may use a less sensitive scale targeted for specific injuries. Hence, a severity scale is environment and work specific, and also has the subjective input of the severity rater. Severity has so far been quantified by experts and analysts based on their experience and the environmental inputs. The Accident Frequency-Severity Chart (AFSC) developed by Priest (1996) enables severity to be rated according to the type of injuries, financial loss based on injuries and damaged equipment, on the same scale. This scale has been developed for high risk outdoor activities. Higher numbers on the scale indicate higher degrees of loss. Priest (1996) suggests that the acceptability of these ratings should be decided by a committee of experienced personnel in this field; however, these may be done individually.

2.6 Potential Severity

The discussed severity scales measure the severity of accidents. Injuries need to occur before cases are rated for severity. There are near accident cases where individuals could have sustained serious injuries, but were spared from injury by a very small margin. There will be a severity associated with near accidents if they become accidents. The situation in which a near accident occurs could result in a major accident in the future. Potential severity is the subjective severity rating given to potential losses caused by near accidents. The potential losses can be in the form of physical injury, cost of damaged equipment or similar degrees of loss. Hence, these situations must be analyzed in order to determine the causal factors of near accidents.

The concerns that needed to be addressed while rating potential severity included: How can we assign a particular type of injury to a particular situation? For example, how can we know what type of injury could occur if an object strikes an employee in the head with considerable force and velocity? Currently, there is no established procedure for rating potential severity. The ratings are given according to the rater's subjective view (Davidson, 2004). A physician can imagine the types of injuries that could occur if near accidents become accidents. A safety expert can judge the environmental and mental conditions that most likely result in an accident. A manager can estimate the cost incurred if the incident occurs. An employee can be trained to describe the situation as accurately as possible. Each near accident should then be reviewed by all four individuals and a consensus reached on a potential severity rating. This should be the approach for rating incidences for potential severity.

2.7 Human Error

Human error has been defined as an inappropriate or undesirable human decision or behavior that reduces, or has the potential of reducing, effectiveness, safety or system performance (Sanders & McCormick, 1992). Some actions that can be attributed to human error would be viewed as appropriate in some systems, until they cause an incident and the mistake is discovered (Rasmussen, 1979). Another thought is that, an action might become an error only because the action is performed in an unkind environment that does not permit detection and reversal of the behavior before an unacceptable consequence occurs (Rasmussen, 1982). Human Error can then be defined as an action that fails to meet some implicit or explicit criterion (Sheridan, 2008). 70 to 80 percent of all accidents in aviation occur, at least partly, due to human error. (Shappell & Wiegmann, 1996).

Human error has been classified according to type, such as errors of commission, omission, sensing, remembering, deciding and responding (Sheridan, 1992). Errors of commission are caused by incorrectly performing an act. Errors of omission are caused when there is a failure to do something. A sequence error is caused when a task is performed out of sequence. A timing error is caused when there is failure to perform a task within an allotted time period. Further, some authors have classified error based on how information is processed (Rouse & Rouse, 1983). In this system, errors are identified as they occur at different stages of information processing. Information processing occurs in the following stages: Observation of the state of a system, formulating a hypothesis, testing a hypothesis, choosing a goal, selecting an appropriate procedure and lastly, execution of the procedure to achieve the goal. When a system is being observed, for example, there could be incorrect readings of appropriate state variables, or there could be a failure to observe any state variables at all. Further in the process, there may be similar errors in hypothesis testing, choice of a goal, choice of a procedure and the execution of the procedure. The various types of human error have been classified as causal factors to unfavorable incidences in the HFACS.

2.8 Human Factors Analysis and Classification System (HFACS)

The Human Factors Analysis and Classification System (HFACS) has been developed by Shappell and Wiegmann (2000) in order to methodologically categorize causes of incidents. A similar approach to HFACS has been to classify errors based on the type or the level of behavior involved (Rasmussen, 1982). These behaviors have been classified as skill-based, knowledge-based and rule-based behaviors. Errors in skill-based behavior are errors in executing an action. Errors in rule-based behavior are errors in correctly applying preset rules to a situation. Errors in knowledge-based behavior are due to improper assessment of potential hazards in an unusual situation. An unfavorable incident occurs when an employee performs an act that is undesirable in that situation, which leads to injury. However, the reason for this failure to act correctly is more than on an active level (Reason, 1990). The physical environment, supervision and leadership, and the organization as a whole, may also be responsible for the employee to perform an undesired action. For example, the work environment may be too dark for an employee to perform a given task correctly, which may lead to an accident. Investigating further, one could find that the supervisor had not updated the employee on the conditions of the work environment. Further, this investigation could find questionable management policies responsible.

In light of the different organizational levels of causality, Reason (1990) proposed that there are active and latent failures. Active failures are apparent, and can be quickly attributed to have caused the accident. For example, an employee may not be wearing a mandatory hard-hat, and a head injury occurs. This is the lowest level in the accident causation structure. On the other hand, latent failures are failures which occur at higher organizational levels, such as the ones in supervision and organizational management. Latent failures are not apparent at the time of the incident, but come into the spotlight once an investigation occurs. Reason compared each level to a swiss-cheese slice, with the holes in the slice corresponding to the failure at each level. The accountability for each incident can be traced back through the holes in each slice. The failure accountability goes higher up the organizational hierarchy as holes in higher level swiss-cheese slices align.

Using this as a reference, HFACS was developed to elaborate on both the active and latent failures. There are four levels of failure, according to the hierarchy in an organization. Failure on the lowermost level is attributed to unsafe acts (refer to Fig.1). Unsafe acts include errors and violations. Decision based errors are errors that an employee commits due to a consciously thought of action going wrong. For example, an employee may use improvised tools or equipment in an unusual situation and an injury occur from this action.

Skill-based errors are caused when an employee performs a task or action with inadequate skill. For example, an employee may lift an object with improper technique, causing an injury to the back. Perceptual errors are caused when the auditory or visual senses do not function correctly due to external influences. For example, an employee may misjudge the passing clearance under a wire between two electrical poles and cause an electrical arcing incident. Violations are willful and blatant acts against mandatory regulations, and may lead to high severity accidents.

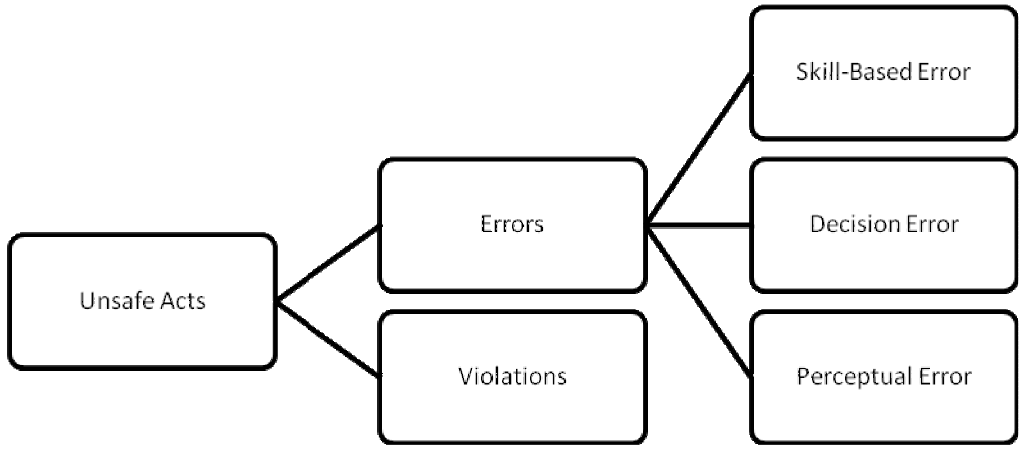

Fig.1 Unsafe Acts (Shappell & Wiegmann, 2000)

Preconditions to unsafe acts is the causal category which explains the creation of a hazardous environment which causes an incident (refer to Fig.2). These preconditions include slippery work surface, temperature and weather conditions. Faulty and non-functional equipment also constitute a precondition if they are a part of the technological environment before an incident occurs.

Unsafe leadership is another level of failure further up the organizational hierarchy (refer to Fig.3). This includes inadequate supervision, planned inappropriate actions, failure to correct known problem and supervisory violations. All these deal with substandard supervision practices at the work environment.

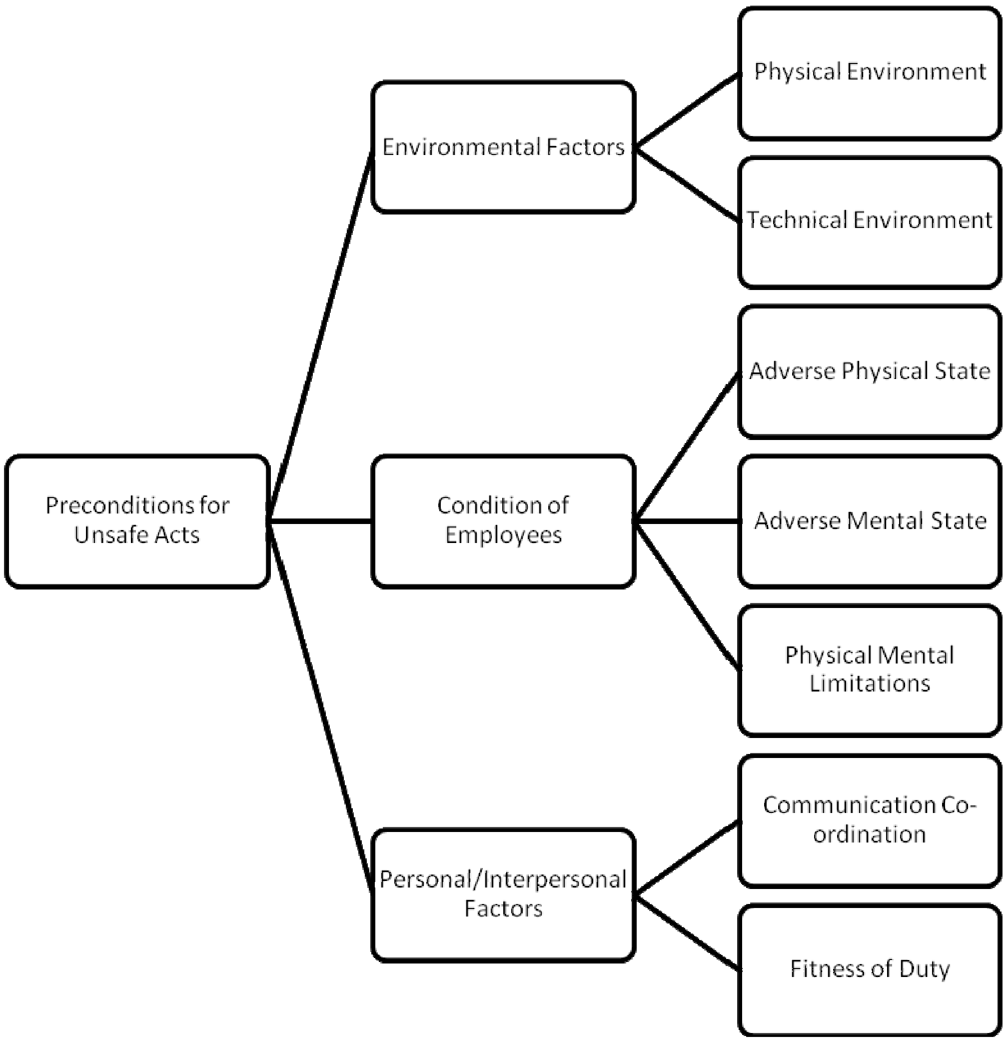

Fig.2 Preconditions to Unsafe Acts (Shappell & Wiegmann, 2000)

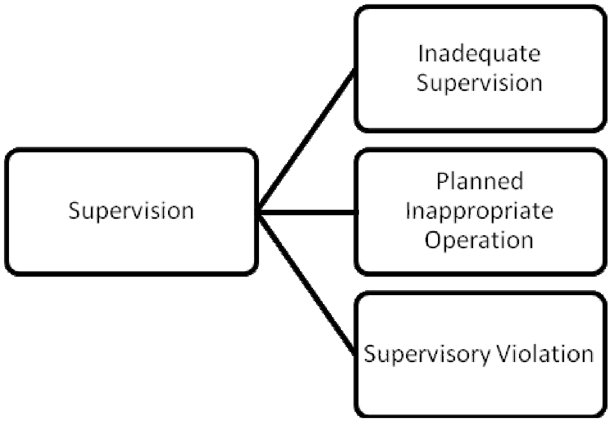

Fig.3 Supervison (Shappell & Wiegmann, 2000)

The highest organizational failure is at the senior management level (refer to Fig.4). The failures at this level are related to poor safety culture as a whole. Failures at this stage stem from lack of funding, human resources problems such as poor background checks on employees and other current company policies. Violations at latent levels result in serious consequences on the management.

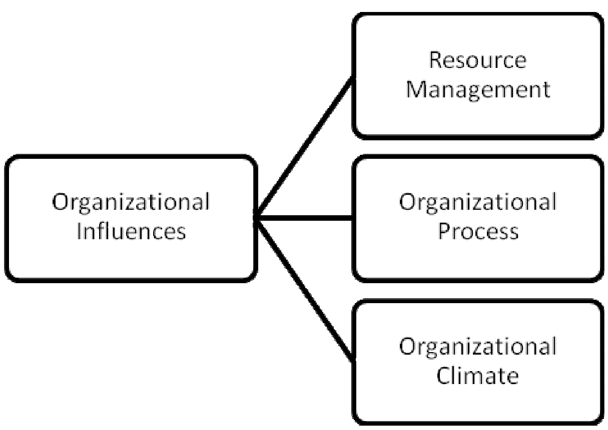

Fig.4 Organizational Influences (Shappell & Wiegmann, 2000)

The HFACS system hence provides the analyst with a set of all possible causal factors that can help identify the causes of the incident. The HFACS causal codes will be used in order to accurately identify causal factors of incidences in the selected work environment in this study. Organizational influences, precondition to unsafe acts, unsafe supervision and unsafe acts are called the four levels of failure (Shappell & Wiegmann, 2000). There are three causal categories, resource management, organizational climate and organizational process. These causal categories have been further divided into specific causal factors called nanocodes. The specific causes of incidents can be identified accurately by referring to a list of nanocodes (refer to Appendix B).

CHAPTER THREE

LOGISTIC REGRESSION

As discussed earlier, we require specific mathematical tools for developing a model which relates incident severity and incident causal factors. Hence, logistic regression techniques and terminologies associated with them will be presented in this chapter.

3.1 What is logistic regression?

Logistic regression is a regression technique employed to fit accident systems. Logistic regression techniques have been used to model probabilistic systems to predict future events. These models are direct probability models that have no requirements on the distributions of the explanatory variables or predictors (Harrell, 2001).

If p is the probability that a binary response variable $Y = 1$ when input variable $X = x$, then the logistic response function is modeled as:

$$p = P(Y = 1|X = x) = \frac{e^{\beta_1 + \beta_0 x}}{1 + e^{\beta_1 + \beta_0 x}}$$

This function represents an s-shaped curve and is non-linear. Here, β is the coefficient of the predictor or input variable x used in a regression equation. A simplified version of this function can accommodate for multiple input variables and is linear. This function is called the logistic regression function and is superior to the logistic response function (Chatterjee & Hadi, 2006):

$$p = P\left(Y = 1 \middle| X = x_1, \dots, X_p = x_p\right) = \frac{e^{\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_p x_p}}{1 + e^{\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_p x_p}}$$

This equation calculates the probability of the response variable to be 1, given multiple predictor variables. This model is still non-linear, and is transformed into linearity by using the logit response function. The equation for logistic response function then becomes:

$$\frac{p}{1-p} = e^{\beta_0+\beta_1 x_1+\beta_2 x_2+\cdots+\beta_p x_p}$$

The term $\frac{p}{1-p}$ in the above equation is called as the odds ratio of the event. Taking the natural logarithm on both sides,

$$log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_p x_p$$

Since, L.H.S. is a function of $x_1,\ldots,x_p$:

$$g(x1, \ldots, xp) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_p x_p$$

The above equation is linear and can be used to determine relationships between variables of interest.

Some studies have used logistic regression modeling to determine the relationship between crash severity and factors which cause crashes. Dissanayake and Lu (2002) determined that presence of certain input variables such as influence of alcohol, point of impact and lack of judgment increase the probability of a crash occurring with higher severity. A variable contributing to a crash was coded 1, else 0. Severity was rated as a non-incapacitating or an incapacitating injury and coded 0 or 1 respectively. *P(Y=1)* was the probability that a crash occurs which results in an incapacitating injury.

As discussed earlier, Li and Bai (2008) used Crash Severity Index (CSI) as a measure of incident severity. They have used logistic regression as a basis of modeling their system. Their approach is similar to that used by Dissanayake and Lu (2002). This technique has been used to estimate the influences of driver, highway, and environmental factors on run-off-road crashes (McGinnis, Wissinger, Kelly, & Acuna, 1999). It has been used to determine the personal and behavioral predictors of automobile crash and injury severity (Kim, Nitz, Richardson, & Li, 2000). Chang and Yeh (2006) used this technique to identify the most contributing risk factors for motorcyclist fatalities. In these studies, the authors have used the environmental and behavioral causes of the incidences as predictors.

3.2 Linear regression versus logistic regression

In linear regression, the relationship between two variables is in the form of:

$$Y = \alpha + \beta X$$

In the above equation, α is known as the intercept, or the value of Y when $X = 0$. β is known as the slope or the change in Y when X increases by one unit. The method used for estimating the values of α and β is known as ordinary least-squares regression (OLS). This method produces the estimates of all the above terms as well as an error term e_j. The error term is the difference between the estimate of Y and Y for case j. The predicted values of the dependent variable Y are well within the range of possible values of Y (Menard, 2001). When the dependent variable is dichotomous, it can carry only two values, 0 or 1. Since the variable is coded in a binary manner, the mean of the predicted values of the dichotomous variable lies between 0 and 1. Hence, the mean of this variable can be interpreted as a function of the probability that a selected case will fall into the higher of the two categories for this variable (Menard, 2001). When the dependent variable is dichotomous and OLS regression is used to estimate the terms, the predicted values of this dependent variable can exceed 1 or can be less than 0. The values of probability always lie between 0 and 1, and OLS regression predicts values of the dependent variable that do not fall in this range.

In logistic regression analysis, the interest is not to directly predict the intrinsic value of the dependent variable Y but to determine the probability that an event will occur. $Y = 1$ indicates that the event has occurred, and $P(Y=1)$ indicates the probability that it will occur. The problem of having predicted values exceed 1 or be less than zero can be avoided utilizing the concept of odds ratio discussed earlier. An odds ratio is the ratio of $Y = 1$ to $Y \neq 1$. For example, if the odds ratio is 1.59, then it indicates that an observation is 1.59 times more likely to fall in a category $Y = 1$ than $Y = 0$. Odds ratios cannot have values less than zero, but can have values more than one.

Hence, OLS cannot be used to determine the probability that an accident will occur with a particular level of severity.

3.3 Ordinal logistic regression

The response variable can have more than two ordered levels. The interest may be to determine the probability that the response will be one of these levels. When there are three or more ordered categories of the response variable, ordinal logistic regression (OLR) method is used for modeling (Chatterjee & Hadi, 2006). The dichotomous dependent variable in binary logistic regression has two levels, 0 and 1. The ordinal response variable has three or more distinct levels increasing in magnitude. An ordered logit model has the form:

$$log\left(\frac{p_1}{1-\ p_1}\right)=\ \alpha_k+\ \beta' X$$

$$log\left(\frac{p_1+\ p_2}{1-\ p_1-\ p_2}\right)=\ \alpha_k+\ \beta' X$$

.
.
.

$$log\left(\frac{p_1+\ p_2+\ \ldots+\ p_k}{1-\ p_1-\ p_2-\ \ldots\ -\ p_k}\right)=\ \alpha_k+\ \beta' X$$

OLR is a logistic regression technique that fits two or more regression curves simultaneously. The equation series above, for example, indicates the odds of belonging to the group represented by $Y\ = 1$ against belonging to the groups represented by $Y\ = 2$ to k. The numbers of equations modeled in this series are the number of ordered categories minus one. If Y has 3 ordered levels, the number of equations modeled are 2. Each such equation represents its own logit model, and hence the individual equations are called logits. The sum of the probabilities from p_1 to p_k is 1. Hence, OLR models cumulative probability. One important assumption in modeling with OLR is that, the relation between independent variables and logits is the same for in all the equations in the series (Norusis, 2008). The assumption implies that the coefficients of the independent variables will not vary significantly. Hence, the variable coefficients β' in all the equations in the series are the same. However, each equation has a different constant term α_k.

3.4 Measures of a good fit

3.4.1 Log-likelihood:

Let the log-likelihood of the model with only the constant term be denoted by L_0 and the one with the independent variables and the constant term be L_1. For binary logistic regression, the -2 log-likelihood (-2LL) is given by (Menard, 2001):

$$L_0 = \{(n_{Y=1})ln[P(Y = 1)] + (n_{Y=0})ln\ [P(Y = 0]\}$$

The -2LL will then be -2 (L_0). Here, N are the total number of cases, $n_{Y=1}$ indicates the total number of cases where $Y=1$. Also, $P(Y=1)$ is $n_{Y=1}/N$. L_1 is represented by the same equation, but the values of the terms will be different due to the inclusion of independent variables. If the model is fit with the constant term only, it is a subset of the model with variables. Hence the former model is said to be nested within the latter. The difference in L_0 and L_1 when multiplied by -2 is interpreted as a chi-square statistic. Hence, the difference between the -2LL values of L_0 and L_1 is interpreted as a chi-square statistic. However, the models must be nested for the difference to be a chi-square statistic. This statistic if, if denoted by χ^2, is given by:

$$\chi^2 = -2(L_0 - L_1)$$

χ^2 tests the null hypothesis that the coefficients of the variables in the model are zero. Hence, if χ^2 is statistically significant ($p < 0.05$), the null hypothesis is rejected. Rejecting the null hypothesis means that the variables enable the model to make better predictions than the model without variables. For an ordinal response variable, the same equations are used, but the difference is the type of event probability. In binary logistic regression, it is *P(Y=1)*, whereas in ordinal the value of 1 is replaced by an ordered category (Menard, 2001). The values of -2LL should be as small as possible in order for the model to be a good predictor.

3.4.2 Cox and Snell R^2 and Nagelkerke R^2

For dichotomous variables, the Cox and Snell R^2 and Nagelkerke R^2 statistics provide the geometric mean squared improvement per observation (Menard, 2001).

$$Cox\ and\ Snell\ R^2 = 1 - (\frac{D_0}{D_1})^{\frac{2}{N}}$$

$$\boldsymbol{Nagelkerke\ R^2} = \left[\mathbf{1} - \left(\frac{\boldsymbol{D_0}}{\boldsymbol{D_1}}\right)^{\frac{2}{N}}\right] / [\mathbf{1} - (\boldsymbol{D_0})^{\frac{2}{N}}]$$

Here, *N* are the total number of cases. If the model fits the data perfectly, the value should be 1, but Cox-Snell R^2 statistic does not take this value. The Nagelkerke R^2 statistic adjusts the Cox-Snell R^2 statistic to take the value of 1. Both statistics are used for measuring the strength of association between dependent and independent variables.

3.4.3 Pearson's χ^2 and Deviance

For ordinal regression, Pearson's statistic is used along with Deviance as an indication of goodness-of-fit. Both values should be small and the significance values large. The large significance value ($p > 0.05$) indicates that the null hypothesis is rejected and the model is a good fit (Norusis, 2008).

All possible dependent variables are cross-tabulated with the independent variable. A row or column is dedicated for each level of every variable. The frequency of cases belonging to i^{th} row and j^{th} column is placed in the observed cell O_{ij} and the expected values predicted by the model are placed in the cell E_{ij} (Kanji, 1994). The Pearson Chi-square statistic and Deviance is given by the equations (Kanji, 1994; Norusis, 2008):

$$\chi^2 = \sum_{i=1}^{p} \sum_{j=1}^{q} \frac{(O_{ij} - E_{ij})^2}{E_{ij}}$$

$$\boldsymbol{D = 2 \sum_{i=1}^{p} \sum_{j=1}^{q} O_{ij} \ln \left(\frac{O_{ij}}{Eij}\right)}$$

There are *p* rows and *q* columns to the table, and the degrees of freedom are reduced to *(p-1(q-1)*.

3.4.4 Test for parallel lines:

For ordinal regression, the regression coefficients are assumed to be the same for all logits. The test for parallelism checks this assumption. The null hypothesis here is that the coefficients of the variables are the same across all response categories. A high significance value ($p > 0.05$) indicates that the null hypothesis cannot be rejected. These tests have been used in SPSS PLUM and SPSS LOGISTIC REGRESSION procedures for checking model goodness of fit and validating model assumptions.

3.4.5 Wald's statistic

Wald's statistic is given by the equation (Menard, 2001):

$$W_k{}^2 = [\frac{b_k}{S.E.of\ b_k}]^2$$

Here, b_k is the variable coefficient value and *S.E.* is the standard error in estimating the coefficient. This statistic can be distributed asymptotically as a χ^2 distribution. Also, it follows standard normal distribution when it is just W_k. This formula parallels the t-ratio for variable coefficients in OLS. This statistic checks how well each predictor contributes to the model individually. Hence, a statistically significant Wald's statistic for a variable indicates that it should be retained in the model.

Hosmer and Lemeshow (1989) suggest that these significance values should be set higher than the conventional levels of 0.05 or 0.1 to values such as 0.2 or 0.25. Many authors (Mickey & Greenland, 1989; Bendel & Afifi, 1977) have used this criterion for screening variables, since they believe that stricter levels such as $p < 0.05$ fail to identify all the important variables. In a study by Dales and Ury (1978), it was determined that setting significance levels well above the conventional values such as 0.05 or 0.1 reduces the possibility of a type II error in variable selection.

CHAPTER FOUR

METHODOLOGY

The initial chapters laid a foundation for the development of the mathematical model to relate incident severity and incident causal factors. This chapter will include the step by step procedure which was used for developing this model. Each sub-procedure will be discussed before presenting its execution with the given data.

4.1 Selecting cases

The incident report from a power generation company was used as the source of data. This report has more than five hundred cases. Only incidences related to maintenance and service activities of the wind turbine generator were considered for further analysis. Incidences involving a vehicle or occurring off premises were not considered for further analysis. For the whole data set, 275 of the incidences were chosen at random using MINITAB software. The remaining 130 the cases were used for validating the model.

4.2 Rating severity

Each selected case was rated for potential and actual severity. As discussed earlier, the involved employee, the physician, the engineer and the manager should reach a consensus while rating potential severity. However, it was not possible to assemble a team which included the employee involved, the site physician and an on-site safety expert. Hence, for future studies, the suggested methodology can be used. Also, there is no established procedure for rating severity in the literature so far.

An interesting perspective on assigning severity has been highlighted by Davidson (2004). Firstly, potential severity ratings were given according to the author's subjective view of what could have materialized out of the perceived hazards at that time. Accident Frequency Severity Chart (AFSC) (Priest, 1996) was used to rate actual severity. This chart was used as a guiding tool in order to assign a potential severity rating.

This effective technique was used for rating potential severity in this study. The AFSC was also used for rating actual severity according to the injuries sustained as described in the incident report. The increasing magnitude of severity according to injury type has been shown in the adapted AFSC (refer to table-1). This order was followed while rating incidences for potential severity. The potential severity was rated for each case by the author. Potential severity was also rated for the cases where employees had sustained actual injuries. This was done by increasing the actual severity by one or more depending on the perceived hazards of the situation as described in the incident report. The severity was rated based purely on the possible injury sustained by the involved employee.

Table 1- Accident Severity Scale (Priest, 1996; Davidson, 2004):

Severity Ranking	Injury	Impact on Participation
1	Splinters, insect bites, stings	Minor
2	Sunburn, scrapes, bruises, minor cuts	
3	Blisters, minor sprain, minor dislocation Cold/heat stress	
4	Lacerations, frostbit, minor burns, mild concussion, mild hypo/ hyperthermia	Medium
5	Sprains & hyper-extensions, minor fracture	
6	Hospital stay < 12 hours fractures, dislocations, frostbite, major burn, concussion, surgery, breathing difficulties, moderate hypo/ hyperthermia	Major
7	Hospital stay > 12 hours e.g., arterial bleeding, severe hypo/ hyperthermia, loss of consciousness	
8	Major injury requiring hospitalization e.g., Spinal damage, head injury	Catastrophic
9	Single death	
10	Multiple fatality	

The incident report included descriptions of the condition in which the incidences occurred. These included near accidents as well as accidents involving actual injuries. Many cases in the incident report were already rated for severity. The injury ratings given for these cases were used to rate for the other cases. For near accidents, the potential severity was rated by considering the situation where the employee would have been injured rather than just spared from injury. For example, an employee could be on top of a three hundred foot high wind turbine tower with inadequate fall protection equipment. In such a case, potential severity was given according to the worst possible outcome. For this example, the employee could fall from a height which could prove fatal.

Consistency was maintained while rating cases of similar nature. For example, a possible fatal fall from 300 feet was always rated as 9, whereas a possible fall of 20 feet was rated as 6 (Please refer table 1). Cases involving other types of injuries were also rated in the same manner (refer to tables 2, 3, 4, 5 and 6). The environmental parameters such as falling height, type of object, electric current voltage were given in the incident report. However, some cases did not report these important data. For such cases, the worst possible outcome was assumed.

Table 2- Potential severity assigned to falling objects

List of falling objects:	Potential Severity: (Falling height one deck 20 feet)	Potential Severity: (Falling height 300 feet)
Wrench	6	9
Phone	4	6
Radio	6	9
Hydraulic torque wrench	6	9
Hammer	6	9
Oil filter and bucket	6	9
Space plate	6	9
Hard case	6	9
Winch nut snap ring	2	4
Unopened soda can	4	6
Crane hook	6	9
Voltmeter	6	9
Latch handle	6	9
Piece of crane boom	6	9
Battery	3	5
Bolt	2	4
Nut	2	4
Slip ring	2	4
Grease gun	6	9

Table 3- Potential severity assigned to slips and falls

Description	Potential Severity
Fall is from height of 300 feet.	9
Fall is from 20 feet	6
Employee slips and falls on a hard metal surface	6

Table 4- Potential severity for electrical cases:

Voltage	Potential severity in case of contact with live wire	Potential severity in case of burns sustained from arc flashing
575	9	8
480	9	6
400	9	6
220	9	6
100	8	6
24	4	2

Table 5- Potential severity assigned to impact cases:

Object(s)	Part of body	Potential Severity
Torque wrench	Fingers Brow	6 6
Wrench	Toes	6
Hatch, Opening	Fingers between	7
Heavy metal parts	Fingers between	7
Stepladder, Own weight	Fingers between	7
Hydraulic wrench reaction arm, nut, bolt	Fingers between	7
Rotor lock, wrench	Fingers between	7
Heavy cable (suspended), ladder rung	Fingers between	7
Mast, nacelle	Fingers between	7
Axis cabinet support and rotating gear	Foot	7
Ladder rung	Elbow Wrist	7 7
Gearbox	Ribs	7
Buss bar	Elbow	7
Sledge Hammer	Single finger	8
Chisel	Knee	7
Hammer	Knee Little finger tip	7 8
Torque multiplier	Forearm	7
Hatch	Forehead	8

Table 6- Potential severity assigned to Real Injuries:

Diagnosed cases:	Actual Severity	Potential Severity
Bursitis in the elbow	6	7
Sprain in the right ring finger	4	5
Laceration to right thumb	5	6
15 mm laceration on his brow	7	8
Contusion to hand and foot Left hand	6	7
Heavy sudden lifting damage to the back	5	6
Laceration to the back of the head	7	8
Laceration wound left leg (grinding wheel)	6	8
Contusion on left maxilla	6	7
Laceration to the head requiring 10 staples	7	8
Laceration requiring three sutures mid cranial back of head	7	8
Laceration to the finger	5	6
Contusion to left ankle	6	7
3 inch laceration on the forehead req. 2 internal and 4 external stitches.	7	8
Fractured Finger, some cuts on the others	7	8
Finger crushed, thumbnail removed	8	8

Lastly, the incident report also did not include the financial loss incurred for these cases. Hence, it was not possible to develop an actual severity scale which incorporated both physical injury and the cost to the organization. Hence, both the potential and actual severities were rated based solely on physical injuries.

4.3 Arranging data

MS EXCEL worksheets were used to arrange the preliminary data and assign causal categories to each case. The original incident report had each case assigned a causal category according to HFACS methodology. Each selected case had a case ID assigned in the original incident report. The selected cases with their ID were arranged in one column. Individual columns were assigned to the 18 causal categories. Columns were also assigned to potential and actual severity. A 1 was registered in the cell with the row representing the case ID and column representing the causal category identified for the case. If two causal factors (nanocodes) of the same causal category were assigned to a single case, it was only counted once in the corresponding cell. 275 of the cases were chosen at random using MINITAB. Data from these cases was used for model construction.

4.4 Constructing the model

There are ten levels by which the actual and potential severities were rated. Hence, there were two or more ordered levels by which both types of severities could be rated. There were dichotomous variables representing the causal categories and ordinal variables with more than two levels representing actual and potential severity. Ordinal logistic regression models determine the probability of an observation to fall into a specific group, when there are two or more ordered levels of the dependent variable. Binary logistic regression models calculate the probability of an observation to fall into one of two groups, when there are two levels of the dependent variable. Hence, it was suitable to construct the models using ordinal logistic regression. The initial approach was to construct two ordinal regression models, one with actual severity as the dependent variable and the other with potential severity. The dependent variables had ten ordered levels of severity. The initial models included all the contributing variables (refer to tables 7 and 8). However, none of the models passed the test of parallel lines, which determines if the variable coefficients are the same for all logits in the ordinal logistic regression model (refer to tables 9 and 10).

Table 7- Initial Potential Severity Model Parameters

	Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
[psev = .00]	-5.141	1.703	9.112	1	.003	-8.479	-1.803
[psev = 3.00]	-1.966	1.400	1.972	1	.160	-4.709	.778
[psev = 4.00]	-.554	1.396	.157	1	.692	-3.291	2.183
[psev = 5.00]	.014	1.398	.000	1	.992	-2.726	2.754
[psev = 6.00]	.654	1.400	.218	1	.641	-2.091	3.398
[psev = 7.00]	1.175	1.402	.703	1	.402	-1.572	3.922
[psev = 8.00]	1.595	1.402	1.294	1	.255	-1.153	4.342
[psev = 9.00]	6.564	1.689	15.098	1	.000	3.253	9.874
[de=.00]	.684	.312	4.787	1	.029	.071	1.296
[de=1.00]	0[a]	.	.	0	.	.	.
[se=.00]	.504	.294	2.939	1	.086	-.072	1.080
[se=1.00]	0[a]	.	.	0	.	.	.
[v=.00]	-1.823	.590	9.533	1	.002	-2.981	-.666
[v=1.00]	0[a]	.	.	0	.	.	.
[pte=.00]	.371	.271	1.876	1	.171	-.160	.901
[pte=1.00]	0[a]	.	.	0	.	.	.
[f=.00]	1.310	1.039	1.592	1	.207	-.725	3.346
[f=1.00]	0[a]	.	.	0	.	.	.

a. This parameter is set to zero because it is redundant.

Table 8- Initial Actual Severity Model Parameters

	Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval Lower Bound	Upper Bound
[asev = .00]	-3.846	2.367	2.639	1	.104	-8.486	.794
[asev = 1.00]	-2.772	2.359	1.381	1	.240	-7.396	1.851
[asev = 3.00]	-2.000	2.354	.722	1	.395	-6.613	2.612
[asev = 4.00]	-.550	2.356	.054	1	.815	-5.167	4.067
[asev = 5.00]	2.039	2.533	.648	1	.421	-2.925	7.004
[de=.00]	-1.248	.335	13.847	1	.000	-1.906	-.591
[de=1.00]	0[a]	.	.	0	.	.	.
[se=.00]	-.994	.322	9.508	1	.002	-1.626	-.362
[se=1.00]	0[a]	.	.	0	.	.	.
[pte=.00]	-.529	.293	3.267	1	.071	-1.103	.045
[pte=1.00]	0[a]	.	.	0	.	.	.
[f=.00]	-1.964	1.050	3.497	1	.061	-4.022	.095
[f=1.00]	0[a]	.	.	0	.	.	.
[pe=.00]	-2.454	.836	8.620	1	.003	-4.092	-.816
[pe=1.00]	0[a]	.	.	0	.	.	.
[ams=.00]	2.109	1.021	4.262	1	.039	.107	4.111
[ams=1.00]	0[a]	.	.	0	.	.	.
[cc=.00]	-2.596	.547	22.485	1	.000	-3.669	-1.523
[cc=1.00]	0[a]	.	.	0	.	.	.
[is=.00]	2.512	1.443	3.030	1	.082	-.316	5.341
[is=1.00]	0[a]	.	.	0	.	.	.

a. This parameter is set to zero because it is redundant.

Table 9- Initial Potential Severity Model Test of Parallel Lines

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Null Hypothesis	195.373			
General	.000[a]	195.373	35	.000
The null hypothesis states that the location parameters (slope coefficients) are the same across response categories.				
a. The log-likelihood value is practically zero. There may be a complete separation in the data. The maximum likelihood estimates do not exist.				

Table 10- Initial Actual Severity Model Test of Parallel Lines

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Null Hypothesis	171.583			
General	.000[a]	171.583	32	.000
The null hypothesis states that the location parameters (slope coefficients) are the same across response categories.				
a. The log-likelihood value is practically zero. There may be a complete separation in the data. The maximum likelihood estimates do not exist.				

Murad, Fleischmann, Sadetzki, Geyer and Freedman (2003) have suggested collapsing categories in order to improve the number of observations in individual categories and hence improve model parameter approximations in ordinal logistic regression models.

For potential severity ratings, ten ordered levels were hence collapsed into three ordered levels. The values were divided in these three levels. Ratings from 0 to 4 were collapsed into the lowermost level. Hence, the ratings from 0 to 4 were coded as 0. Severity ratings from 5 to 7 were collapsed into the middle level and 8 to 10 in the highest level. These ratings were coded as 1 and 2 respectively.

There are 18 distinct causal categories. Each category represents an independent variable used in the model. The variables which did not contribute towards the occurrence of any incident at all were eliminated from further analysis. These variables were *pml*, *sv*, *oc*, *fcp* and *pis* (refer to Appendix A.).

The remaining variables were selected for fitting in further models. The initial model for potential severity included all the contributing variables (refer to table-11). Variables which had their Wald's statistic significant at a p-value < 0.25 were selected for fitting in the next model (refer to tables-12 and 13). The procedure continued till all variables and constants had a significant Wald's statistic (refer to table- 14). The final model for potential severity included four causal categories (refer to table- 15). The models were constructed on SPSS v.17.0. SPSS PLUM ordinal logistic regression procedure was utilized for fitting the models. For the variables in the final model, two-way, three-way and four-way interactions were investigated for their contribution to the model. These interactions were added in the model. There were no cases where five or more causal categories were identified at once, and hence higher level interaction terms were not included in the models.

Table 11- Model 1 Parameter Estimates

	Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
[ordinal1 = .00]	1.121	2.867	.153	1	.696	-4.499	6.741
[ordinal1 = 1.00]	2.847	2.874	.982	1	.322	-2.785	8.480
[de=.00]	.834	.353	5.587	1	.018	.142	1.525
[de=1.00]	0[a]	.	.	0	.	.	.
[se=.00]	.474	.325	2.131	1	.144	-.163	1.111
[se=1.00]	0[a]	.	.	0	.	.	.
[pe=.00]	.605	.862	.492	1	.483	-1.086	2.295
[pe=1.00]	0[a]	.	.	0	.	.	.
[v=.00]	-1.690	.668	6.395	1	.011	-3.000	-.380
[v=1.00]	0[a]	.	.	0	.	.	.
[ppe=.00]	.401	.334	1.442	1	.230	-.253	1.054
[ppe=1.00]	0[a]	.	.	0	.	.	.
[pte=.00]	.552	.299	3.402	1	.065	-.035	1.138
[pte=1.00]	0[a]	.	.	0	.	.	.
[ams=.00]	.238	.596	.160	1	.689	-.930	1.407
[ams=1.00]	0[a]	.	.	0	.	.	.
[aps=.00]	1.052	1.369	.591	1	.442	-1.631	3.736
[aps=1.00]	0[a]	.	.	0	.	.	.
[cc=.00]	.479	.551	.756	1	.385	-.600	1.558
[cc=1.00]	0[a]	.	.	0	.	.	
[f=.00]	1.198	1.106	1.174	1	.279	-.969	3.366
[f=1.00]	0[a]	.	.	0	.	.	.
[is=.00]	-1.459	1.035	1.987	1	.159	-3.488	.570
[is=1.00]	0[a]	.	.	0	.	.	
[rm=.00]	.393	.735	.286	1	.593	-1.048	1.835
[rm=1.00]	0[a]	.	.	0	.	.	.
[op=.00]	-.171	1.097	.024	1	.876	-2.321	1.978

[op=1.00]	0[a]	.	.	0	.	.	.
a. This parameter is set to zero because it is redundant.							

Table 12- Model 2 Parameter Estimates

	Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
[ordinal1 = .00]	-1.344	1.820	.545	1	.460	-4.910	2.223
[ordinal1 = 1.00]	.372	1.821	.042	1	.838	-3.197	3.942
[de=.00]	.806	.339	5.653	1	.017	.142	1.471
[de=1.00]	0[a]	.	.	0	.	.	.
[se=.00]	.372	.312	1.424	1	.233	-.239	.983
[se=1.00]	0[a]	.	.	0	.	.	.
[v=.00]	-1.587	.632	6.309	1	.012	-2.826	-.349
[v=1.00]	0[a]	.	.	0	.	.	.
[ppe=.00]	.365	.329	1.235	1	.266	-.279	1.009
[ppe=1.00]	0[a]	.	.	0	.	.	.
[pte=.00]	.486	.291	2.779	1	.096	-.085	1.057
[pte=1.00]	0[a]	.	.	0	.	.	.
[f=.00]	1.113	1.103	1.019	1	.313	-1.048	3.275
[f=1.00]	0[a]	.	.	0	.	.	.
[is=.00]	-1.267	1.003	1.596	1	.207	-3.233	.699
[is=1.00]	0[a]	.	.	0	.	.	.
a. This parameter is set to zero because it is redundant.							

Table 13- Model 3 Parameter Estimates

	Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
[ordinal1 = .00]	-2.559	1.362	3.528	1	.060	-5.229	.111
[ordinal1 = 1.00]	-.849	1.358	.391	1	.532	-3.512	1.813
[de=.00]	.756	.335	5.075	1	.024	.098	1.413
[de=1.00]	0[a]	.	.	0	.	.	.
[se=.00]	.337	.309	1.185	1	.276	-.270	.943
[se=1.00]	0[a]	.	.	0	.	.	.
[v=.00]	-1.629	.631	6.671	1	.010	-2.864	-.393
[v=1.00]	0[a]	.	.	0	.	.	.
[ppe=.00]	.340	.328	1.076	1	.300	-.302	.982
[ppe=1.00]	0[a]	.	.	0	.	.	.
[pte=.00]	.472	.291	2.637	1	.104	-.098	1.041
[pte=1.00]	0[a]	.	.	0	.	.	.
[is=.00]	-1.263	1.002	1.589	1	.207	-3.228	.701
[is=1.00]	0[a]	.	.	0	.	.	.

a. This parameter is set to zero because it is redundant.

Table 14- Variable Selection

Variable	Model 1	Model 2	Model 3	Final Model
de	Included	Included	Included	Included
se	Included	Included	Not-Included	Not-Included
pe	Included	Not-Included	Not-Included	Not-Included
v	Included	Included	Included	Included
ppe	Included	Included	Included	Not-Included
pte	Included	Included	Included	Included
ams	Included	Not-Included	Not-Included	Not-Included
aps	Included	Not-Included	Not-Included	Not-Included
pml	Not-Included	Not-Included	Not-Included	Not-Included
cc	Included	Not-Included	Not-Included	Not-Included
f	Included	Not-Included	Not-Included	Not-Included
is	Included	Included	Included	Included
pis	Not-Included	Not-Included	Not-Included	Not-Included
sv	Not-Included	Not-Included	Not-Included	Not-Included
rm	Included	Not-Included	Not-Included	Not-Included
oc	Not-Included	Not-Included	Not-Included	Not-Included
op	Included	Not-Included	Not-Included	Not-Included
fcp	Not-Included	Not-Included	Not-Included	Not-Included

Table 15- Final Model Parameter Estimates

	Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval Lower Bound	Upper Bound
[ordinal1 = .00]	-3.466	1.187	8.529	1	.003	-5.792	-1.140
[ordinal1 = 1.00]	-1.765	1.177	2.249	1	.134	-4.072	.542
[de=.00]	.475	.256	3.433	1	.064	-.027	.977
[de=1.00]	0[a]	.	.	0	.	.	.
[v=.00]	-1.845	.596	9.580	1	.002	-3.013	-.677
[v=1.00]	0[a]	.	.	0	.	.	.
[pte=.00]	.298	.254	1.384	1	.239	-.199	.795
[pte=1.00]	0[a]	.	.	0	.	.	.
[is=.00]	-1.186	.996	1.417	1	.234	-3.139	.767
[is=1.00]	0[a]	.	.	0	.	.	.

a. This parameter is set to zero because it is redundant.

There were no high severity accidents that resulted in injuries which could be rated between 8 and 10. Hence, the actual severity levels could be collapsed into two categories. Actual severity ratings between 0 and 4 were collapsed into the 0 category. Actual severity ratings between 4 and 7 were collapsed into the 1 category. The variable representing actual severity now consisted of two ordered levels. Hence, a binary logistic regression model with the binary levels of actual severity was fit with the causal categories as independent variables (refer to table- 16). Only the variables which had their Wald's statistic significant at $p < 0.25$ were selected in the final model. The final model for actual severity consisted of only three significant variables (refer to table- 17).

The interaction effects between these variables were also added to this model. SPSS LOGISTIC REGRESSION procedure was used for testing interactions.

Table 16- Pilot Model for Actual Severity

Variable	β	S.E.	Wald	df	Sig.
de	.503	.566	.790	1	.374
se	.407	.540	.570	1	.450
pe	1.977	1.006	3.865	1	.049
v	.252	.854	.087	1	.768
ppe	.486	.501	.941	1	.332
pte	.078	.486	.026	1	.873
ams	-.717	1.136	.398	1	.528
aps	1.906	1.490	1.637	1	.201
cc	2.235	.643	12.074	1	.001
f	-18.859	23152.665	.000	1	.999
is	-18.857	17912.582	.000	1	.999
rm	-18.778	14292.210	.000	1	.999
op	-19.362	23152.665	.000	1	.999
Constant	-2.518	.581	18.781	1	.000

Table 17- Final model for actual severity

Variable	β	S.E.	Wald	df	Sig.
pe	1.724	.935	3.396	1	.065
aps	2.129	1.429	2.221	1	.136
cc	2.129	.572	13.856	1	.000
Constant	-2.129	.204	109.384	1	.000

4.5 Validating the model

The cases used for validation were the remaining 130 not used earlier for constructing the model. Each case had been rated for potential and actual severity. The probability that a case with given input variables has a particular potential severity rating was determined using the formulae in table 18 (Norusis, 2008):

Each case where one or more of the variables from the group *de, is, pte* and *v* were identified as causal categories could provide the inputs 0 or 1 for the equations. Cases where these variables were not identified as causal categories were not selected for validation, since this meant that the coefficients of all the variables in the equations would be zero. The eliminated variables have coefficients which are not significant statistically, and hence do not contribute to the model. Cases were categorized as being correctly predicted if the calculated probability was above 0.85. For example, (refer to table- 19) for a particular case, *v* was identified as a causal category and the severity rating given belonged in the middle level (potential severity between 5 and 7). The low probability calculated (0.35, <0.85) classified this case as not correctly predicted.

Table 18- Probability Formulae(1)

Probability	Formula
P(severity of an incident will be in a specific category j)	$p\begin{pmatrix} severity\ of\ the\ incident\ will\ be\ in\ categories \\ less\ than\ and\ equal\ to\ j \end{pmatrix} - p(severity\ of\ the\ incident\ will\ be\ in\ categories\ less\ than\ j)$
P(severity of an incident will be in categories less than and equal to j)	$\frac{1}{1+e^{-(\alpha_j-\beta x)}}$ *
P (severity of incident will be between 0-4)	$\frac{1}{1+e^{-[(-3.466)-0.475de+1.845v-0.298pte+1.186is)]}}$
P (severity of incident will be between 5-7)	$[\frac{1}{1+e^{-[(-1.765)-0.475de+1.845v-0.298pte+1.186is)]}} - \frac{1}{1+e^{-[(-3.466)-0.475de+1.845v-0.298pte+1.186is)]}}]$
P (severity of incident will be between 8-10)	$1-\frac{1}{1+e^{-[(-1.765)-0.475de+1.845v-0.298pte+1.186is)]}}$
* α_j : Constant value in for the categories j β : Variable coefficient x : Variable value (Either 1 or 0). Variables were *de*, *v*, *pte* and *is*.	

Table 19- Model validation examples:

Case	Given potential Severity rating	Collapsed potential Severity group	Given Ordinal category	Predicted probability that severity will be between			Correctly Predicted?
				0-4	5-7	8-10	
1	4	0-4	0	0.165	0.355	0.480	No
2	8	8-10	2	0.02	0.077	0.903	Yes

In another case, the causal category *de* and severity rating belonging highest level (severity between 8 and 10) was given. The high calculated probability value (0.903, > 0.85) classified this case as being correctly predicted for potential severity.

For the actual severity model the probability of belonging to the highest group (probability of severity between 4 and 7) was calculated using the equation in table- 20 (Menard, 2001). The procedure used for the validation of the potential severity model was also applied for validating the actual severity model.

Table 20- Probability Formulae (2)

General Formula	$P(Y=1) = \dfrac{e^{\alpha+\beta_1 X_1+\beta_1 X_1+\cdots+\beta_k X_k}}{1+e^{\alpha+\beta_1 X_1+\beta_1 X_1+\cdots+\beta_k X_k}}$
P(severity of incident will be between 4 and 7)	$P(Y=1) = \dfrac{e^{-2.129+1.724pe+2.129aps+2.129cc}}{1+e^{-2.129+1.724pe+2.129aps+2.129cc}}$
P(severity of an incident will be between 0 and 3)	$P(Y=0) = 1 - \dfrac{e^{-2.129+1.724pe+2.129aps+2.129cc}}{1+e^{-2.129+1.724pe+2.129aps+2.129cc}}$
* α : Constant value β : Variable coefficient x : Variable value (Either 1 or 0). Variables were *pe*, *aps* and *cc*.	

CHAPTER FIVE

RESULTS AND CONCLUSION

In this section, the results of this study will be presented along with its limitations. Future works will be discussed based on the lessons learnt from this study.

5.1 Results

The various measures of model fitting discussed earlier were used as indicators of how well a model fits the data. The final potential severity model had four variables (refer to table- 14). Each variable had statistically significant Wald's statistics. The test for common slopes was statistically insignificant ($p>0.05$). Hence, the null hypothesis that the coefficients of the variables are the same across all the logits could not be rejected (refer to table- 23). The intercept (constant) values for both the logits showed statistically significant Wald's statistics at a p-value of 0.25. Also, the Pearson Chi-square and Deviance Chi-square values are statistically insignificant at a p-value of 0.05 (refer to table- 22). The null hypothesis that the model does not fit is rejected, and model is a good fit with the chosen variables (refer to table- 21). In the validation stage, it was determined that the potential severity model could predict 35% of the validation cases correctly. However, the model correctly predicted 87% of the cases whose severity was between 8 and 10. Hence, this model can be utilized to determine the probability of high potential severity for incidents.

The variables included in the final model for potential severity were decision error, violation, preconditions to unsafe acts: technological environment and inadequate supervision. Decision Error and preconditions to unsafe acts: technological environment need to be investigated and safety interventions targeted in order to prevent high potential severity incidents in the future. These variable coefficients are positive, and hence the presence of these two causal categories increases the probability of an incident occurring with higher potential severity (refer to table- 15).

For the final actual severity model, all three selected variables had Wald's statistics statistically significant at a p-value of 0.25 (refer to table- 17). The likelihood ratio chi-square statistic has a p-value < 0.05. Hence, the hypothesis that model variable coefficients are zero can be rejected, and the model with the variables fits significantly better than the model without the variables (refer to table- 25). The high -2LL value indicates that the model fits the data poorly and the low Cox and Snell and Nagelkerke R^2 statistic values indicate a small improvement per observation from the null model (refer to table- 24). The actual severity model could not correctly predict the probability of belonging to the higher group (probability of severity between 4 and 7) or the lower group (probability of severity between 0 and 3) for any of the validation cases. The cutoff here was also 0.85, as assumed in the case of potential severity models. Hence, the actual severity model cannot be used for predicting the actual severity of incidents. More incidences need to be reported and the model re-fitted.

There were no interaction terms whose Wald's statistics were found to be statistically significant at a $p < 0.25$ level, for both the actual and potential severity models. Hence these models only included the main effects.

Table 21- Model Fitting Information (Final Model)

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	69.429			
Final	48.088	21.341	4	.000

Table 22- Goodness-of-fit (Final Model)

	Chi-Square	df	Sig.
Pearson	9.869	12	.627
Deviance	11.461	12	.490

Table 23- Test of Parallel Lines (Final Model)

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Null Hypothesis	48.088			
General	44.233	3.855	4	.426

Table 24- Final Model Summary:

-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
200.974[a]	.057	.105

Table 25- Omnibus tests of final model parameters:

	Chi-square	df	Sig.
Step	16.241	3	.001
Block	16.241	3	.001
Model	16.241	3	.001

5.2 Conclusion

In this study, a relation between the HFACS causal categories and incident severity has been modeled using logistic regression. Causal factors that result in high severity incidents have been identified.

The potential severity model can be used as a tool to calculate the probability of high severity incidences. In addition, causal factors which contributed significantly towards incidences with high potential severity were found to be decision error and preconditions to unsafe acts: technological environment. The coefficients of the variables decision error and preconditions to unsafe acts: technological environment were found to be positive. Having these causal categories increases the probability of potential severity. Having a negative coefficient for one of the variables reduces calculated probability of response (Norusis, 2008). Some authors have concluded that having a negative variable coefficient tends to reduce the calculated probability in logistic regression (Dissanayake & Lu, 2002).

Violation and Inadequate supervision were found to have negative variable coefficients. Also, having these variables in the potential severity model reduced the probability of potential severity. For example, having a decision error increases the calculated probability of potential severity between 8 and 10 by 0.049, while a violation reduces the probability by 0.378. The amount change in probability per variable is reflected by the value of the coefficients. For example, decision error changes the calculated probability more than precondition to unsafe acts: technological environment and their coefficient values are 0.475 and 0.298 respectively.

One of the core assumptions in HFACS is that when a causal category is attributed towards an incident, it is responsible partially or fully for that incident to occur. Though the variables attribute towards causing the incident, they may impact the severity differently. The negative variable coefficients for violation and inadequate supervision indicate that these causal categories reduce the calculated probability of potential severity between 8 and 10. Hence, the presence of these variables actually reduces the probability that an incident may occur with a high severity. When there are several causal categories for an incident, some may impact the outcome more significantly than others. As it has been found earlier, a violation tends to reduce the probability of potential severity by 0.378 while a decision error increases it by 0.049. Hence, the presence of some causal categories changes incident severity more than others and some increase the probability of severity while others reduce it.

The actual severity model was not a good fit with the data, and none of the severity levels correctly calculated the probability for the validation cases. Hence, this model cannot be used for calculating the probability of severity.

By identifying such critical causal factors, management will be boosted in the decision making process. Managers can give higher priority for fixing the important causal factors. The developed procedure can be used for predicting severity of future incidents for any work environment. HFACS is a universal classification system which can be applied to multiple work environments. Logistic regression techniques have been successfully applied for predicting actual vehicle crash severity (Dissanayake & Lu, 2002; Li & Bai, 2008) and also in determining causal factors that lead to high severity incidents in coal mines (Maiti & Bhattacherjee, 1999). The work done in this thesis also extends this application to wind turbine generator maintenance activities. In addition, the HFACS system has been used successfully in conjunction with the concept of potential severity.

One of the drawbacks in using logistic regression is that, data from previous cases is required for modeling. Hence, a large number of incidences need to occur in the environment of interest in order to construct the model. Also, probability of severity cannot be determined for incidences with causal categories are not represented by the variables in the final models. Further, the criterion used in variable selection of $p < 0.25$, though supported by previous work in this field (Mickey & Greenland, 1989), will be doubted by researchers who utilize the traditional value of 0.05.

When new incidents are added to the report, the data changes and hence, new models need to be fit for the new data. Hence, the next step is to develop an application which works on a dynamic level by fitting new models automatically and immediately when the incident report changes. Secondly, the severity rated by a physician in conjunction with a safety engineer and the involved employee would be more accurate in terms of damage sustained to the human body and the potential environmental hazards. Hence, in future studies, both types of severities need to be rated for each case with the consent of all involved personnel. There has not been an established procedure to rate potential severity. These drawbacks can be eliminated by developing new techniques which can be used for similar studies in the future.

5.3 Future research

5.3.1 Dynamic model

Once the model is validated using the methodology presented in this paper, it can be used for making future predictions. However, if new incidences occur, the data in the incident report changes and hence new models need to be fit. A constant revision of data should also trigger a constant revision of the model fitting process. This process is shown in the flowchart below (refer to Fig. 5):

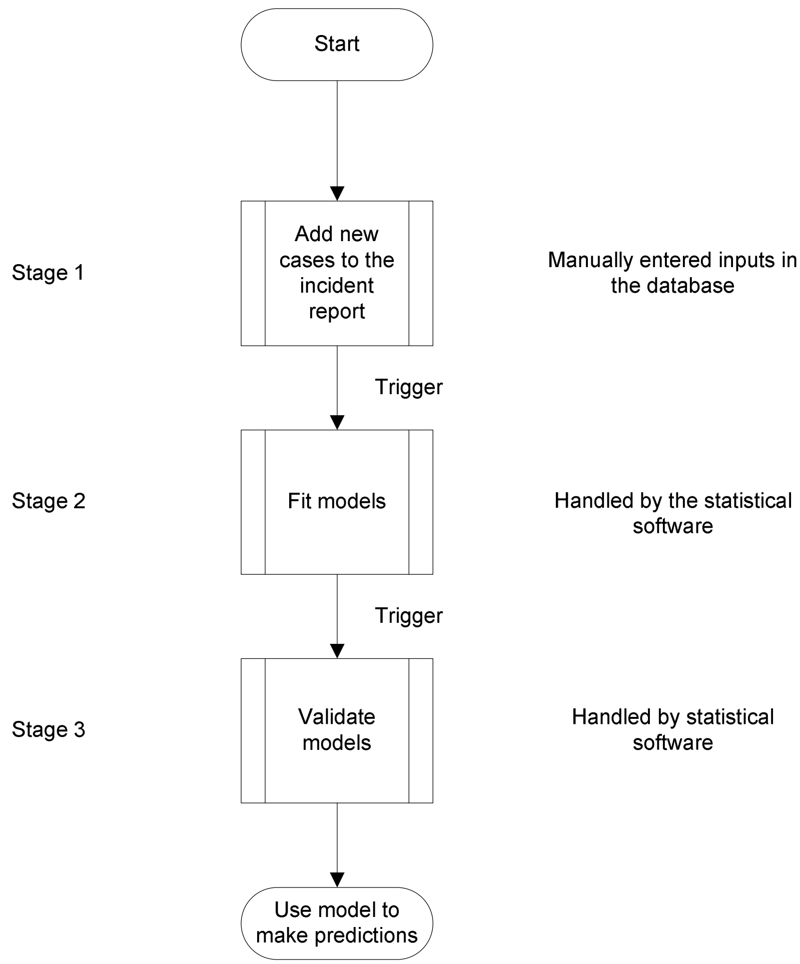

Fig. 5 Dynamic Model

When the database is modified, a trigger starts the methodology for fitting the model as discussed in this study. A change in the incident report triggers the statistical software to follow the model fitting methodology. If the models are a good fit, the validation program is triggered. Otherwise, random samples are chosen till the model fits satisfactorily. The output can then be interpreted by the user. Hence, the next step is the development of a dynamic model where new changes in the incident report trigger a series of programs which fit new models.

Also, once the model had been validated, an interface can be developed which returns the severity probability once the user inputs causal categories. This can be performed in the following manner:

At stage 1 in the figure, the incident report database is modified by simply adding a 1 in the cells with the column representing the identified causal category and the row representing the newly added case ID. Also, potential and actual severity ratings are added in their respective columns for the new case. Once, this occurs an internal program triggers the external statistical software to commence stage 2.

The methodology discussed in this study can be programmed into the statistical software, and all the steps can be executed in the correct fashion. Stage 3 commences once all statistical criteria are verified and the model is a good fit. Otherwise, the model repeats stage 2 till a good fit is found. A custom application can be programmed or a current statistical package customized.

The validation process discussed in this study can be customized with a statistical package or a separate customized software developed. This process will be triggered at the end of stage 2. The output can then be interpreted by the user. An interface can be developed for the output. The user checks the causal factors using the checkboxes. The generate button runs the dynamic model. The output severity levels change as new data is fit, and the interface will reflect these changes. This process is shown in the flowchart below (refer to Fig. 6).

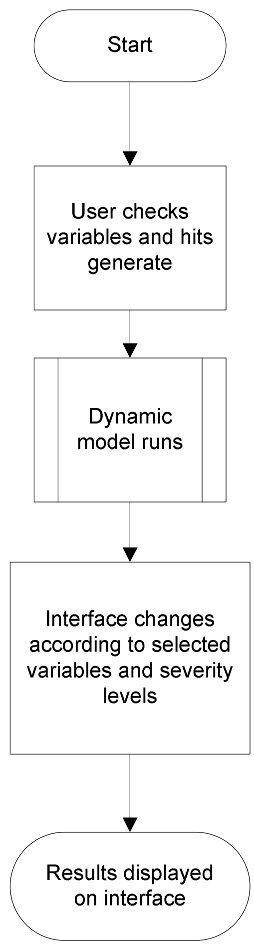

Fig. 6 Interface model

5.3.2 Potential severity rating procedure

There has not been an established procedure for rating potential severity in the literature so far. In previous literature, the potential severity has been rated according to an author's subjective opinion based on the conditions of the incident at that time. In this thesis, potential severity was rated based on the incident description, an actual severity scale and the author's subjective analysis. These subjective ratings may be questioned by decision makers for their validity. This makes the ratings less trusted and their use questioned for further analysis. This is a drawback that needs to be eliminated. Hence, a basic framework needs to be established for rating potential severity. The following step-by-step procedure is proposed (refer to Fig. 7):

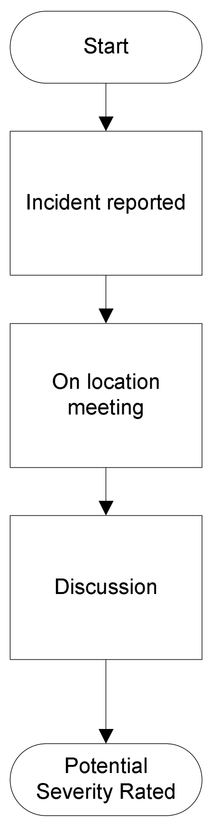

Fig. 7 Potential severity rating procedure

The incident is reported to the safety engineer by the employee involved. The site physician, safety engineer and employee hold an on-site meeting where the incident occurred. The employee now describes the event in detail, according to best recollection.

The employee describes the objects involved, and the energy flows. Also, the position of the employee at the time of the incident is determined.

Next, the safety engineer and the physician discuss the gathered information. The safety engineer determines how the environment would have affected the employee in terms of energy transferred. Energy flow and type have been given importance in analyzing risk by Ross (1981). For example, it could be thermal in the form of hot apparatus, electric in the form of live equipment, in the form of direct impact with an object or a combination of the three. The most probable areas of the body where energy of that magnitude would have transferred are determined.

Further, the site physician determines the possible injuries suffered if the involved employee was contacted in the probable body regions by the energies of that magnitude. Out of the possible injury-body part combination, the physician selects the one that results in most severe injury. The physician rates severity on a ten point scale based solely on physical injury to the employee. The safety engineer and physician have another discussion to ensure they agree on the rating.

The possible workdays lost from the injury are reported by the physician and the possible equipment damaged is reported by the safety engineer to the site or plant manager. Manager calculates the cost to the organization in the event of the incident, based on cost of lost production time and repairs or installation of new equipment. The manager rates the severity of the incident based on possible financial loss. The two ratings are multiplied to combine the effects of both types of severities. This new potential severity rating can be written in the form of:

$$\text{New potential severity rating} = \text{Potential severity Rating based on physical injury} \times \text{Potential severity rating based on financial loss}$$

This new potential severity rating can truly combine severity associated with physical and financial loss. These methodologies can be applied in future studies which use logistic regression techniques for calculating severity probability.

APPENDICES

A. Variable Information

Variable	**Variable Abbreviation**
Unsafe Act: Decision Error	de
Unsafe Act: Skill-based Error	se
Unsafe Act: Perceptual Error	pe
Unsafe Act: Violation	v
Precondition: Physical Environment	ppe
Precondition: Technical Environment	pte
Precondition: Adverse Mental State	ams
Precondition: Adverse Physiological State	aps
Precondition: Physical/Mental Limitation	pml
Precondition: Communication and Co-ordination	cc
Precondition: Fatigue	f
Supervision: Inadequate Supervision	is
Supervision: Planned Inadequate Operation	pis
Supervision: Supervisory Violation	sv
Organizational Influences: Resource Management	rm
Organizational Influences: Organizational Climate	oc
Organizational Influences: Organizational Process	op
Supervision: Failure to Correct Known Problem	fcp

B. List of Nanocodes

Failure Level	Unsafe act
Causal Category	Decision error
Nanocode	Improper use of PPE
	Incorrect or absence of PPE
	Improper use of tool/equipment
	Incorrect tool/equipment
	Inappropriate procedure
	Inadequate knowledge/information
	Exceeded ability

Failure Level	Unsafe act
Causal Category	Skill-based error
Nanocode	Omission of step
	Incorrect operation/handling of tool/equipment
	Equipment drop
	Bad habit/practice
	Attention failure
	Slip, trip, or fall
	Improper use of winch/hoist
	Lifting, lowering, absence of bag, tearing of bag

Failure Level	Unsafe act
Causal Category	Perceptual error
Nanocode	Loss of balance
	Misjudged distance, altitude, clearance, size
	Due to visual illusion

Failure Level	Unsafe act
Causal Category	Violation
Nanocode	Failure to use PPE
	Violation of orders, regulations, SOPs

Failure Level	Preconditions to unsafe acts
Causal Category	Physical environment
	Weather; Extreme heatWeather; extreme cold
	Weather; Ice
	Weather; Rain
	Weather; Snow
	Weather; Windy

Nanocode	Weather; Fog
	Slippery surface
	Poor housekeeping/cleanliness/congestion
	Inadequate lighting
	Presence of hazardous/toxic substances
	Inadequate ventilation
	Altitude
	Terrain
	Unsafe environment created

Failure Level	Preconditions to unsafe acts
Causal Category	Technological environment
Nanocode	Danger zone
	Congested/tight space
	Inappropriate equipment/tool
	Equipment/tool/space design
	Lifting
	Repetitive motion
	Improper posture
	Inappropriate procedure
	Improperly maintained tool/equipment
	3RD party equipment/procedure failure

Failure Level	Preconditions to unsafe acts
Causal Category	Adverse mental states
Nanocode	Mental fatigue
	Circadian dysrythmia
	Complacency/boredom
	Distraction
	Overconfidence/arrogance
	Stress
	Get-home-it is
	Apathy
	Sense of entitlement
	Task saturation
	Rushing

Failure Level	Preconditions to unsafe acts
Causal Category	Adverse physiological states
Nanocode	Physical fatigue
	Illness/sickness
	Intoxication/under an influence

	Effects of medications
	Failure to meet rest requirements while on duty

Failure Level	Preconditions to unsafe acts
Causal Category	Physical/Mental States
Nanocode	Physical limitation
	Visual limitation
	Hearing limitation
	Insufficient reaction time
	Inadequate experience for complexity of situation

Failure Level	Preconditions to unsafe acts
Causal Category	Coordination, communication and planning
Nanocode	Lack of/poor communication or feedback
	Lack of planning/preparation
	Lack of leadership
	Lack of decision-making
	Lack of/poor assertiveness
	Workload management

Failure Level	Preconditions to Unsafe Acts
Causal Category	Fitness for duty
Nanocode	Failure to meet rest requirements
	Self-medicating
	Overexertion while off duty
	Poor dietary practices
	Pattern of poor risk judgment
	Inadequate preparation, skill, or knowledge
	Off duty injury

Failure Level	Supervision
Causal Category	Inadequate Supervision
Nanocode	Failed to provide guidance/oversight
	Failed to track qualifications
	Failed to track performance
	Perceived lack of authority
	Failed to provide adequate rest period
	Lack of accountability
	Failed to provide information/data/ instructions
	Over-tasked/untrained supervisor
	Failed to provide adequate training/on-the-job experience
	Inadequate delegation/prioritization of tasks

	Inadequate provision of PPE
	Excessive tasking/workload
	Inappropriate employee scheduling
	Failed to plan for adequate employee rest
	Failed to provide adequate briefing time /supervision

Failure Level	Supervision
Causal Category	Failed to correct problem
Nanocode	Failed to initiate immediate corrective action
	Failed to report a hazard/problem
	Failed to correct a hazard/problem

Failure Level	Supervision
Causal Category	Supervisory Violation
Nanocode	Knowingly provided inadequate information/ data/instructions
	Authorized unqualified employee for work
	Knowingly failed to enforce rules and regulations
	Knowingly violated procedures
	Willful disregard of authority
	Falsifying documentation/records

Failure Level	Organizational Influences
Causal Category	Resource Management
Nanocode	Insufficient manpower for task
	Inadequate training/qualification system
	Employee selection process
	Lack of funding/excessive cost-cutting
	Failure to correct known design flaws
	Material resource unavailable
	Material resource inappropriate
	Conflicting or too much information/data
	Inadequate prioritization
	3rd party non-compliance

Failure Level	Organizational Influences
Causal Category	Organizational Climate
Nanocode	Policies
	Norms versus rules / policies
	Values, beliefs, attitudes, morale
	Peer pressure
	Communication
	Accessibility / Visibility of supervisor / lead

	Delegation of authority
	Formal accountability for actions
	Promotion
	Unstable workforce (hiring, firing, retention)
	Drugs and alcohol
	Time / quota pressure
	Organizational Structure

Failure Level	Organizational Influences
Causal Category	Operational Process
Nanocode	Instruction inadequate or unclear
	Instruction not documented / available
	Information / data inadequate or unclear
	Information / data not available
	Revision process long / complicated
	Communication of change inadequate
	Reward / recognition / incentives
	Monitoring and checking of resources, climate, and processes inadequate

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