SIGNAL DETECTION THEORY: ENABLING WORK NEAR THE EDGE

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ABSTRACT

Occupational accidents are unquestionably wasteful and non-value adding events in any system of production. Safeguarding construction workers from occupational hazards, whether arising from traumatic, ergonomic, and/or exposure accidents, is part and parcel of the lean construction ideal of waste elimination. Howell et al. (2002) proposed a new approach to understand construction accidents based on Rasmussen's theory of cognitive systems engineering. One aspect of the model focused on worker training to recognize hazards (unsafe conditions). The underlying assumption here is that workers will always recall what constitutes a safe or unsafe situation as well as respond to perceived or actual risks in the same manner. Therefore, a methodology to assess worker sensitivity to unsafe conditions and risk orientation is needed. This paper proposes a methodology based on Signal detection theory that was originally developed as an assessment technique for tasks requiring the detection of defective components in an industrial setting. Discussion of signal detection theory and how it could be tailored for assessments of the sensitivity and risk orientation of construction workers to unsafe conditions is presented. Application of the methodology is demonstrated using a pilot study involving structural steel workers. The methodology presented in this paper could be used to give guidance to workers on how to enhance their abilities to identify the boundary beyond which work is no longer safe.

KEYWORDS

Occupational Safety, Construction Safety, Signal Detection Theory, Construction Accidents, Safety Training

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INTRODUCTION

Each year, occupational injuries (traumatic, ergonomic, and/or exposure) and fatalities in the construction industry temporarily or permanently disable many and claim the lives of others. This problem is receiving increasing attention in the construction industry, as well as in other industries, not because of human suffering alone, but also due to many cost-related factors. Such factors include escalating workers' compensation insurance costs, high direct costs of medical treatment and rehabilitation programs, and high indirect costs, such as administrative costs, productivity losses and lower morale. These factors will increase construction costs, and adversely impact a contractor's competitiveness.

The staggering statistics collected and disseminated by occupational safety and health concerned organizations confirm the impact and importance of this problem. The Center for Protecting Workers' Rights reports that (CPWR 1998): "Construction safety and health death rate – 15 deaths per 100,000 workers, or more than 1000 killed yearly- is more than three time the rate for manufacturing in the United States……The more than 182,000 serious injuries annually in construction in the United States not only waste live and hurt productivity, but also substantially increase payroll costs (through workers' compensation and other costs)."

Occupational accidents are unquestionably wasteful and non-value adding events in any system of production. Similar to other wasteful and non-value adding events that result in unreliable workflow such as late delivery of material and equipment, design errors, change orders, equipment breakdowns, and environmental effects, occupational accidents also result in the same. When left uncontrolled, these factors create havoc on any construction project resulting in either barely meeting the numbers or suffering devastating losses. Howell and Ballard (1994) state that achieving reliable workflow is possible when sources of variability are controlled. It follows then that safeguarding construction workers from occupational hazards, whether arising from traumatic, ergonomic, and/or exposure accidents, is part and parcel of the lean construction ideal of waste elimination.

Unfortunately, decades long efforts to combat occupational accident have stalled and improvements have reached a plateau. This situation reflects a fundamental problem in understanding the accident process. Thus far, most efforts to understand the accident process have failed to recognize the dynamic and dependent nature of construction work (Howell et al. 2002). To include this missing dimension, Howell et al. (2002) proposed a new approach to understand construction accidents based on Rasmussen's theory of cognitive systems engineering (Rasmussen et al. 1994). The model suggested recognizes that organizational and individual pressures push people to work in hazardous situations. These pressures defeat efforts to enforce safe work rules specifically in a changing work environment such as in construction. Therefore, this approach emphasizes the need to train workers to be conscious of hazardous work environments and engage the work with better planning and appropriate protection in a very similar way to how fire fighters engage hazardous situations.

The primary goal of this paper is to introduce a methodology to assess the occupational safety competencies of workers based on individual sensitivity to unsafe conditions and risk orientation. This methodology, which is based on Signal Detection Theory (SDT), enables the implementation of the Rasmussen model by enhancing workers abilities to identify the boundary beyond which work is no longer safe. To this end, the paper introduces and discusses the Rasmussen paradigm for understanding and eliminating accidents. Guided by this new paradigm, the paper develops the SDT-based methodology.

THE RASMUSSEN MODEL

Despite the contributions of construction accident causation models in understanding the accident process, none of the models considered the dynamic nature of construction work and that accident scenarios differ in how they occur from site to site. To include this missing dimension, Howell et al. (2002) proposed a new approach to understand construction accidents based on Rasmussen's theory of cognitive systems engineering.

The original model as proposed by Rasmussen is shown in Figure 1. As shown, Rasmussen divided the work environment to three zones. Zone I, which is the region enclosed by the "Boundary of unconditionally safe behavior", "Organizational Boundary to Economic Failure", and "Individual Boundary to Unacceptable Workload", is considered the safe zone (Rasmussen et al. 1994, Rasmussen 1997).

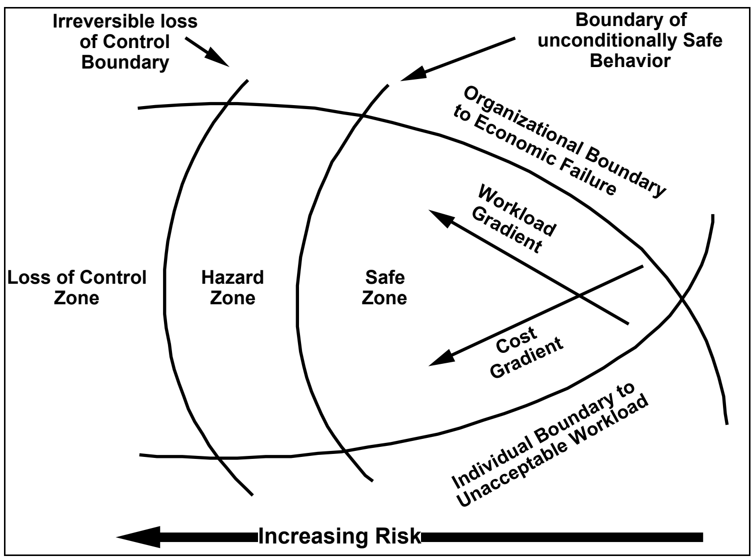

Figure 1: Three Zones of Risk (Howell et al, 2002)

Rasmussen states that due to economic or workload pressures, workers will shift their work along the workload and/or cost gradients, respectively. Both gradients move from a high value to a lower value. Thus, as long as workers remain within the safe zone, work activities can be safely performed. Current safety regulations and management practices are directed at keeping the workers in the safe zone. Rasmussen suggests that enlarging the safe zone through proper planning of operations will make the work safer.

The zone encompassed by the "Boundary of Unconditionally Safe Behavior" and the "Irreversible Loss of Control Boundary" is Zone II or the Hazard zone. Workers working in the Hazard zone are considered to be working at the edge (pushing their luck). Note that the Hazard zone includes hazards that could result in traumatic, exposure, and/or ergonomic type accidents. Rasmussen believes that, despite regulatory or supervisory efforts, workers will move to the Hazard zone due to many reasons. He suggested, contrary to current conventional wisdom, that the only effective way to counter these tendencies to work in the Hazard zone would be to make the boundary beyond which work is no longer safe more visible and to teach workers to recognize the boundary and to cautiously engage the Hazard.

The third and final zone in Rasmussen's model is the loss of control zone where accidents occur and control is lost leading to injuries and/or fatalities. For this zone, Rasmussen proposed that workers should be educated and trained on how to recover from such situations. This is very similar to instructing drivers on how to handle slips on icy roads.

Rasmussen's theory recognizes that organizational and individual pressures will push people to work in hazardous situations. These pressures defeat efforts to enforce safe work rules specifically in a changing work environment such as in construction. Therefore, this approach emphasizes the need to train workers to be conscious of hazardous work environments and engage the work with better planning and appropriate protection in a very similar way to how fire fighters engage hazardous situations.

According to Rasmussen the worker is the best person to judge the boundaries of safe work. So instead of forcing workers to follow the rules and stay in the safe zone, Rasmussen suggested to train workers to:

1. Identify which zone they are working in
2. Identify hazards
3. Prevent hazard release
4. Recover when hazards are released

While counterintuitive, Rasmussen's recommendation to train workers to deal with hazards and recover from scenarios when control is lost recognizes that workers will frequently and inevitably work in the hazard zone. Management pressures and seeking less physical, and perhaps mental, workload effort are realistic examples pushing workers to the hazard zone.

The Rasmussen model is similar to the current trend in the social sciences of using social norms marketing. In this approach, informing people what to do versus the traditional approach of telling people what not to do brings about desired behavioral changes. For example, instructing heavy college-aged drinkers not to drink before driving and citing the grave consequences of such behavior has become an overrated message that lost its effectiveness. Alternatively, social norms marketing follows a tact where people are given instruction on what to do if they would like to drink – To drink moderately and have fun while sparing yourself and others the risks.

While Rasmussen still maintains that safety and performance will increase if the safe zone is enlarged with proper planning, he clearly acknowledges the need to tell workers what to do in the Hazard Zone and when control is lost versus the overrated messages workers hear, e.g., don't dry-cut bricks because you will develop silicosis.

It is worth noting that the Rasmussen model embodies many of the previously developed accident causation models by construction researchers. For example, McClay's 'universal framework' (1989) identified three key elements of accidents: hazards, human actions, and functional limitations that are exceeded in the case of an accident (Rasmussen's hazard zone). Hinze's distraction theory (1996) suggests that the probability of accidents increase when workers are distracted from thinking about their safety due to the stress of work or other factors (Rasmussen's cost and workload gradients). The root cause analysis model by Abdelhamid and Everett (2000) argues that management deficiencies or workers create unsafe conditions in the workplace, and that when faced with unsafe conditions workers either fail or succeed in identifying them (Rasmussen's hazard zone). The 'constraints-response' model developed by Suraji et al. (2001) attributes accidents to distal and proximal factors which cause workers to respond in ways that may lead to accidents (Rasmussen's cost and workload gradients). Toole (2002) suggests eight root causes: lack of proper training, safety equipment not provided deficient enforcement of safety, unsafe equipment, method, or condition, poor safety attitude, and isolated deviation from prescribed behavior (all these conditions lead to losing control in the Rasmussen's Hazard Zone).

The acceptance and effectiveness of Rasmussen's approach remains an open question that only future research can answer. Howell et al. (2002) recommended that future research efforts consider the following three areas:

1. IN THE SAFE ZONE: Establish methods and techniques to enlarge the safe zone.
2. AT THE EDGE: Train workers on the identification of safe and unsafe conditions. And once in an unsafe condition, workers should be trained on how to recover from errors.
3. OVER THE EDGE: People will inevitably make mistakes resulting in loss of control. Hence, measures should be in place to limit the effect of this loss.

This paper is concerned with the second area; "At the Edge". Teaching workers to recognize that they have stepped into the hazard zone appears to be achievable through intensified and directed training. However, a major drawback is that most safety training workshops seldom evaluate comprehension and retention of communicated safety rules and regulations. Hence, it is unreasonable to assume that workers will vividly recall rules and regulations when making a safe/unsafe decision.

Training programs such as Crew Resource Management (CRM) could be used to overcome the passive nature of conventional safety training workshops (Helmreich et al. 1999). CRM primarily evolved as a tool to reduce the number of human-related accidents in the aviation industry. This is not surprising given that the major contributing factor in 80% of commercial aviation accidents is attributed to human error (Federal Aviation Administration 1998). The current generation of CRM training is founded on the fact that human error is inevitable. Accepting this reality, it behooves management to institute an organization-wide safety culture. For an in-depth discussion of CRM topics and techniques, the reader is referred to Helmreich et al. (1999) and Klinect (1999).

The focus on worker training to recognize hazards (unsafe conditions) assumes that workers will always recall what constitutes a safe or unsafe situation as well as respond to perceived or actual risks in the same manner. Regardless of the safety training program adopted, the focus on worker training to recognize hazards (unsafe conditions) frequently overlooks the fact that hazard recognition is contextual and subject to individual judgment and experience. In other words, one worker may consider a situation hazardous while another worker would consider it perfectly safe. Hence, the sensitivity of workers towards unsafe conditions will be different. In addition, the tendency to work in known hazardous situations will depend on a worker's risk orientation. Therefore, a methodology to assess worker sensitivity and risk orientation is needed to give guidance to workers on how to enhance their abilities to identify the boundary beyond which work is no longer safe.

Signal detection theory (SDT) is an assessment technique that was developed for tasks requiring the detection of defective components in an industrial setting. A brief discussion on signal detection theory and how it could be tailored for assessments of the sensitivity and risk orientation of construction workers to unsafe conditions follows.

SIGNAL DETECTION THEORY

In the manufacturing industry, quality inspections are performed to identify and reject (remove) defective products. The inspection problem is also found in other industries or job situations such as detecting a fracture on an X-ray plate by a radiologist, detecting weapons by an airport security guard, and, for the purposes of this paper, identifying unsafe conditions by a construction worker.

An ideal quality inspection process would identify and reject all the defective products. This seldom occurs even with automated inspections. The number of defective products that escape detection (misses) and non-defective ones that are rejected (false alarms) gives a measure of the effectiveness of an inspection process. These two measures have also become the basis for characterizing the sensitivity of the operator (or machine) performing the inspection. Researchers have dubbed the framework leading to such characterization as "Signal Detection Theory" or SDT (Ihara 1993 and Swets 1996).

SDT is applicable in situations where two discrete states of the world (signal and noise) cannot be easily discriminated. In such situations, a human operator (or machine) is faced with the task of identifying one of the states. If the state of the world is a signal, e.g., a defective product, the response of the operator (or machine) is either 'yes' the product is defective (a HIT) or 'no' the product is not defective (a MISS). If the state of the world is noise, e.g., the product is not defective, the response of the operator (or machine) is either 'yes' the product is defective (a FALSE ALARM) or 'no' the product is not defective (a CORRECT REJECTION). These situations are represented as shown in Table 1. Clearly, the perfect result should only have 'hits' and 'correct rejections' – an ideal situation not possible in real life.

Table 1: The four outcomes of signal detection theory (Wickens 1992)

		State of the world	
		Signal	**Noise**
Response	**Yes**	HIT	FALSE ALARM
	No	MISS	CORRECT REJECTION

In a signal detection task, operators sometimes have response biases and are prone to say 'yes' more often than they should thereby detecting most of the signal but also producing many false alarms. The other response could be conservative by saying 'no' and producing fewer false alarms but missing many of the signals (Wickens 1992). Depending on the task, an approach with fewer false alarms may be better than not missing any signal while having many false alarms.

In SDT, the signal indicator or strength is assumed to have a normal distribution (argued using the central limit theorem). It follows then that the information in Table 1 could be graphically represented as shown in Figure 2. Xc, shown in Figure 2, represents the critical level where an observer decides the nature of a signal. In other words, Xc represents the "mental" cut-off the observer uses to decide whether to say 'yes' there is a signal (a hit), or 'no' there is noise (correct rejection).

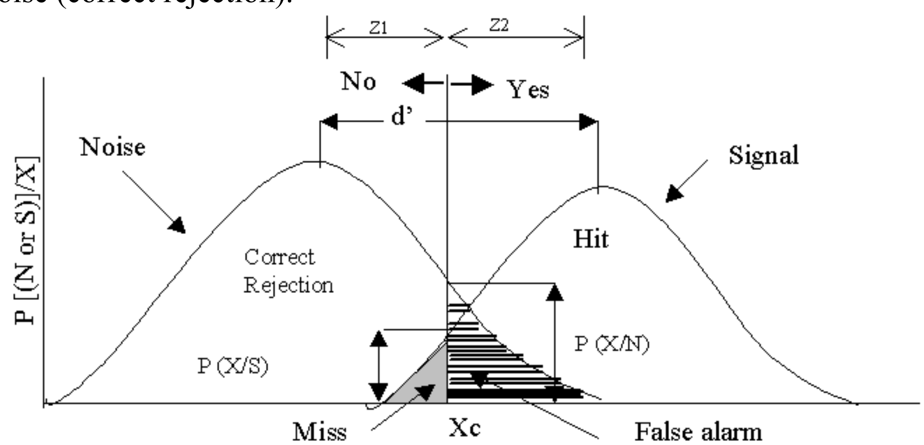

Figure 2: Signal and Noise Distribution (Wickens 1992)

In Figure 2, the shaded portion on the left of Xc represents the missed signals by the observer. The striped portion on the right of Xc represents the signals the observer incorrectly considered as hits, i.e., these are false alarms. The change in the position of Xc determines the respective proportion of misses to false alarms (Swets 1996). For example, if Xc cuts more into the signal side, then most responses will be 'no' resulting in numerous misses and fewer false alarms (as well as fewer hits). If Xc cuts more into the noise side, most responses will be "yes" resulting in fewer misses but more false alarms.

The mental cut-off, Xc, chosen by an observer is quantified using a parameter termed the response criterion or likelihood ratio and is denoted as $\beta_{current}$. This parameter has also been termed the judgment or decision criterion of the observer. Mathematically, and as shown in Figure 2, $\beta_{current}$ is the ratio of the ordinates P (X/S) and P (X/N) for a given level of Xc. P (X/S) and P (X/N) represent the conditional probability of Xc given a signal and the probability of Xc given noise, respectively. $\beta_{current}$ is calculated using Equation 1.

$$\beta_{current} = \frac{P(X/S)}{P(X/N)} \tag{1}$$

High values of $\beta_{current}$ indicate a high number of misses, whereas a lower one will generate more false alarms. Because of inter-observer variability with respect to the choice of Xc, evaluating the results of multiple observers requires the normalization of the value of $\beta_{current}$ or the comparison to an optimal value. The optimal value for β has been taken as the value corresponding to a minimum number of errors, i.e. minimum misses and false alarms. Mathematically, this value is the ratio of the probability of noise, P(N), and the probability of a signal, P(S). Equation 2 gives this ratio.

$$\beta_{opt} = \frac{P(N)}{P(S)} \qquad (2)$$

After finding the value of $\beta_{current}$ and β_{opt}, the pair are compared to determine whether an observer is following a risky or conservative strategy. On the one hand, When $\beta_{current}$ is greater than the value of β_{opt}, this indicates that Xc is positioned more to the right resulting in less false alarms and more misses. According to SDT literature, observers with such a mental-cutoff require more evidence to say 'yes, a part is defective', i.e., they're less likely to say 'yes'. Operators adopting this strategy are considered conservative because they produce few false alarms, i.e., they reject fewer non-defective parts. On the other hand, when $\beta_{current}$ is less than β_{opt} this indicates that Xc is positioned more to the left resulting in more false alarms and less misses. Under SDT, this indicates that the observer needs considerably less evidence to say 'yes, a part is defective', i.e., they're more likely or quick to say 'yes'. This strategy is considered risky because more false alarms will occur, i.e., the operator will reject more non-defective parts. The underlying assumption in considering a strategy as conservative or risky is the cost of a false alarm compared to that of a miss. To summarize, the rules for $\beta_{current}$ and β_{opt} are as follows:

$$\beta_{current} > \beta_{opt}\text{; strategy is conservative} \qquad (3)$$
$$\beta_{current} < \beta_{opt}\text{; strategy is risky} \qquad (4)$$

Another important measure of an observer's performance in signal detection tasks is sensitivity to the signal and the noise. This is measured by the degree of separation between the means of the two distributions shown in Figure 2 and is denoted as d′. A high value of d′ indicates a high degree of separation and, thus, high observer sensitivity. Data from numerous tasks indicate that d′ ranges in value from 0.5 to 2.0 (Wickens 1992).

The value of d′ is determined by adding the two values z_1 and z_2 shown in Figure 2. z_1 and z_2 represent the value of the standard normal variable corresponding to the probability of a false alarm and probability of a miss, respectively. The values are readily available from standard tables. The application of SDT will be demonstrated using an example of a typical inspection process.

EXAMPLE

A manufacturer produces DC motors using a process that generates 5% defectives. In response to increasing customer complaints, the manufacture instituted a final inspection system that finds 80% of defective motors at the expense of falsely rejecting 1% of good motors. Determine the sensitivity of the operator and the strategy he/she adopts.

Using the provided information, the following probabilities can be deduced:

P (Noise) = P (product is not defective) = 95% = 0.95

P (Signal) = P (product is defective) = 5% = 0.05
P (Hit) = 0.80 P (Miss) = 1-P (Hit) = 0.20
P (FA) = 0.01 P (CR) = 1- P (FA) = 0.99

Calculation of the sensitivity, i.e., the value of d′, involves the standard normal values z_1 and z_2. Using the P (FA) and P (Miss) and the standard normal table, the values of z_1 and z_2 are:

$z_1 = 2.326$
$z_2 = 0.842$

and $\Theta\ d' = z_1 + z_2 \therefore d' = 2.376 + 0.842 = 3.168$. This indicates[5] a high degree of separation between the signal and noise distributions, i.e., the inspector has high sensitivity.

As indicated by Equation 1, calculating $\beta_{current}$ requires the determination of P (X/S) and P (X/N). However, Figure 2 indicates that:

P (X/S) = Ordinate corresponding to z_2
P (X/N) = Ordinate corresponding to z_1

Using standard statistical tables, P (X/S) and P (X/N) are as follows:

Ordinate corresponding to $z_2 = 0.28$
Ordinate corresponding to $z_1 = 0.027$
$\therefore \beta_{current} = 0.28 / 0.027 = 10.37$

Using Equation 2, β_{opt} is:

$$\beta\ opt = \frac{P(N)}{P(S)} \Rightarrow \beta\ opt = \frac{0.95}{0.05} = 19$$

Because $\beta_{current} < \beta_{op}$ the strategy is considered risky. This means that the inspector's cut-off level, Xc, is positioned more to the left, i.e., cuts more in the signal distribution.

CONSTRUCTION UNSAFE CONDITIONS AND SDT

Similar to inspection (detection) tasks in other industries, in construction, workers are expected to identify whether the condition they are working in is safe. In SDT, the state of the world is represented by a signal and noise. From a construction safety standpoint, the state of the world is either an "Unsafe" condition (signal) or a "Safe" condition (noise).

When a particular condition is known to be "safe" and a worker is asked whether the condition is *unsafe*, one of two responses is possible, namely, 'Yes' condition is unsafe (false alarm), or 'No' condition is safe (correct rejection). Conversely, when facing a known "unsafe" condition and a worker is asked whether the condition is *unsafe*, one of two responses may be given, namely, 'Yes' condition is unsafe (Hit), or 'no' condition is safe (Miss). Table 2 shows the SDT matrix for these scenarios.

The ideal scenario is for a worker to correctly identify the unsafe and safe conditions. Some workers may be capable of this but others will incorrectly consider a condition as safe while it is unsafe, and vice versa. Signal detection theory allows the determination of the sensitivity of workers to safe (or unsafe) conditions as well as their inclination (bias) to consider a situation as safe (or unsafe) while it is not.

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5 $d' \le 0.5 \Rightarrow$ low sensitivity; $0.5 < d' \le 2 \Rightarrow$ moderate sensitivity; $2 < d' \Rightarrow$ high sensitivity

Table 2: The SDT matrix for detection of unsafe conditions in construction

		State of the world	
		Unsafe Condition (Signal)	**Safe Condition** **(Noise)**
Response (Q: Is condition unsafe?)	**Yes**	HIT	FALSE ALARM
	No	MISS	CORRECT REJECTION

As explained before, d′ and beta (current and optimum) are the SDT parameters or metrics used to assess a worker's sensitivity to unsafe and safe conditions as well as the inclination to consider a condition as safe or unsafe. High values of d′ indicate high sensitivity in differentiating safe from unsafe conditions. Conversely, low values of d′ indicate that a worker needs more training to recognize the two conditions.

Regardless of the value of d′, the mental cutoff used by a worker to decide the state of a condition is given by the value of $\beta_{current}$ with respect to β_{opt}. However, considering the implementation of SDT in construction, interpreting the values of $\beta_{current}$ and β_{opt} requires a modification.

As discussed before, a $\beta_{current}$ value greater than β_{opt} indicates a conservative strategy because few false alarms and many misses will result. Similarly, a value of $\beta_{current}$ smaller than β_{opt} is considered a risky strategy because many false alarms and few misses will result. However, in construction, the cost of a miss could result in a fatality or a serious injury. Therefore, in construction, having more false alarms and fewer misses would be a conservative strategy while having fewer false alarms and more misses would be a more risky strategy. Accordingly, the construction-equivalent for rule (3) and (4) take the following form:

$$\beta_{current} > \beta_{opt}\text{; strategy is risky} \qquad (5)$$

$$\beta_{current} < \beta_{opt}\text{; strategy is conservative} \qquad (6)$$

Assessing worker performance in detecting unsafe and safe condition in real time is difficult and may be dangerous for both workers and observers. The alternative is to survey workers about whether they consider a particular situation unsafe. This approach will allow the assessment of the occupational safety competency of a worker but not the tendency of a worker to work in a condition despite knowing its unsafe. To assess whether a worker would work in a condition despite being unsafe requires a technique such as CRM wherein on-the-job performance is monitored by an observer.

Table 3, shows a sample survey, with ideal answers, designed using part of the Occupational Safety and Health Administration (OSHA) fall protection standards (see Toole and Gambatese (2002) for a primer on OSHA). An OSHA inspector provided assistance in developing the survey questions. For each question, the worker chooses from one of three responses: a) Condition is unsafe; b) Condition is safe; c) I Don't know. The survey was primarily intended as a pilot and, therefore, is neither comprehensive nor exhaustive. To illustrate the use and analysis of the survey, five ironworkers (average age was 32 and average construction experience was 8 years) were selected at random to complete the survey.

The result for one of the workers is shown in Table 4. Based on the responses, the number of hits, misses, false alarms, and correct rejections are determined and converted to probabilities. For example, if a question portrayed a safe condition and the worker's response was 'unsafe condition' or 'I don't know', then this was considered a false alarm. If the question portrayed an unsafe condition and the worker's response was 'safe condition' or 'I don't know', then this was considered a miss. A hit or a correct rejection results when the worker correctly identifies an unsafe condition as unsafe or a safe condition as safe.

Table 3: Sample Construction SDT Survey

INTERVIEW QUESTIONS	**RESPONSE**		
	Condition is Unsafe	**Condition is Safe**	**I Don't Know**
1) Working on a 130 ft high coupler scaffold designed by your company's foreman.	X		
2) Working on a scaffold that is 8 feet above the lower level with no fall protection.		X	
3) Working on a scaffold 10 feet above the lower level with no fall protection.	X		
4) While bolting and welding is taking place for the 1st floor of a 10-story building, you were asked to start work on perimeter beams on the 4th floor.	X		
5) Working on the 13th floor of a building where permanent floors have been installed to the 6th floor only.	X		
6) Working on a 3,500 sqft decking when you know it is unsecured.	X		
7) Working on a 3,000 sqft decking when you know it is unsecured.		X	
8) A 50-inch square opening was created during the renovation of a flat roof.	X		
9) Working on a 2,500 sqft decking when you know it is unsecured.		X	
10) While bolting and welding is taking place for the 1st floor of a 10-story building, you were asked to start work on perimeter beams on the 3rd floor.		X	

Table 4: Sample survey analysis results

		State of the world	
		Unsafe Condition (Signal)	**Safe Condition (Noise)**
Response (Is condition unsafe?)	**Yes**	HIT = 1	FALSE ALARM = 1
	No	MISS = 3	CORRECT REJECTION = 5

Note that:

P (Noise) = P (safe conditions) = 4/10 = 40%
P (Signal) = P (unsafe condition) = 6/10 = 60%.

P (Hit) = 1/4   P (Miss) = 1-P (Hit) = 3/4
P (FA) = 1/6   P (CR) = 1- P (FA) = 5/6

Calculation of the sensitivity, i.e., the value of d′ involves the standard normal values z_1 and z_2. Using the P (FA) and P (Miss), the values of z_1 and z_2 are:

- $z_1 = 0.994$ and $z_2 = 0.674$
- $\Theta d' = z_1 + z_2 \quad \therefore d' = 0.994 + 0.674 = 1.668$

Because d′ typically falls between 0.5 and 2[6], the value of d′ for this worker indicates a moderate degree of separation between the signal and noise distributions, i.e., the worker has moderate sensitivity. To calculate $\beta_{current}$ and β_{opt} , the ordinates corresponding to z_1 and z_2 are determined:

- Ordinate corresponding to $z_2 = 0.318$
- Ordinate corresponding to $z_1 = 0.243$
- Using Equation 1: $\beta_{current} = 0.318 / 0.243 = 1.31$
- Using Equation 2: β_{opt} = P (Noise) / P (Signal) = 0.4/0.6 = 0.67

$\Theta\beta_{current} > \beta_{opt} \Rightarrow$ the worker is using a risky strategy, i.e., the worker will have more misses than false alarms (see rules 5 and 6).

Table 5 lists the results for the 5 workers surveyed in this study. As shown in Table 5, the results don't vary on sensitivity of the workers but 4 out of 5 have a risky strategy, i.e., they have more misses than false alarms. It is worth noting that none of the workers selected option 'c'. While the sample size is quite small to facilitate statistical analysis and inferences, aggregation of results may not be necessarily meaningful other than for group characterization. Individual scores of workers will serve as better input to training design.

[6] $0.5 \le d' < 1.0 \Rightarrow$ low sensitivity; $1.0 \le d' < 1.5 \Rightarrow$ moderate sensitivity; $1.5 \le d' \Rightarrow$ high sensitivity

Table 5: Sample survey analysis results

Worker	D'	Sensitivity	$\beta_{current}$	Strategy
1	1.68	Moderate	1.31	Risky
2	1.05	Moderate	1.98	Risky
3	0.68	Moderate	3.2	Risky
4	1.56	Moderate	1.05	Risky
5	1.38	Moderate	0.35	Conservative

The above example illustrates how the sensitivity and risk orientation of a worker can be determined. This information sets a benchmark against which the effectiveness of new training can be assessed. Essentially, this information would make it possible to determine if a worker's sensitivity and risk orientation towards safe and unsafe conditions increased, decreased, or remained unchanged. Ultimately, the use of SDT will result in increasing workers abilities to judge the boundary beyond which work is no longer safe.

CONCLUSION

The Rasmussen model for accident causation presented in this paper departs from conventional thinking that workers or management are at fault for accidents and that through informing each side what to do and how to perform, safety will be improved. The model states that organizational and individual pressures push people to work in hazardous situations and that these pressures cannot be ignored nor magically relieved through worker training and enforcement of safety regulations. The model indicates that workers will inevitably choose to work or find themselves forced to work in the hazard zone. Therefore, management must adopt a social norms marketing approach and train workers on how to work with hazards and how to regain control once it's lost.

Implementation of the Rasmussen model will require a concerted effort on the part of both academia and industry. Future research should be guided by the strategy recommended in Howell et al (2002), which, at the expense of being repetitious, is reproduced here:

1. IN THE SAFE ZONE: Establish methods and techniques to enlarge the safe zone.
2. AT THE EDGE: Train workers on the identification of safe and unsafe conditions. And once in an unsafe condition, workers should be trained on how to recover from errors.
3. OVER THE EDGE: People will inevitably make mistakes resulting in loss of control. Hence, measures should be in place to limit the effect of this loss (safety net).

This paper discussed the use of Signal Detection Theory as an enabler for worker's behavior "At the Edge". The methodology presented allows the assessment of a worker's occupational safety competency. It also facilitates the evaluation of training efforts directed at teaching workers how to identify the zone (condition) they are working in. However, as used in this paper, the SDT assessment does not provide evidence of whether a worker would in fact proceed with work after identifying an unsafe condition. This important issue can be assessed using CRM techniques.

Additional research is needed to develop surveys for other types of construction work and investigate the relation between age and work experience and occupational safety competency. Other researchers may choose to further develop the SDT-based method or find other methods from other disciplines or industries. Regardless of the approach, efforts to develop new tools and ideas aimed at improving construction safety and health should be guided by Rasmussen's model.

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