9-2016

A Bayesian-Influence Model for Error Probability Analysis of Combine Operations in Harvesting

Yu Du
Iowa State University, yudu@iastate.edu

Michael C. Dorneich
Iowa State University, dorneich@iastate.edu

Brian L. Steward
Iowa State University, bsteward@iastate.edu

Cameron A. MacKenzie
Iowa State University, camacken@iastate.edu

A Bayesian-Influence Model for Error Probability Analysis of Combine Operations in Harvesting

Abstract
Harvesting is one of the most important agricultural operations because it captures the value from the entire cropping season. In modern agriculture, grain harvesting has been mechanized through the combine harvester. A combine harvester enables highly productive crop harvesting. Combine harvesting performance depends on the highly variable skill of combine operators and associated operator error. An approach was developed to analyze the risk of the combine harvesting operation as it relates to operator error. Specifically, a risk analysis model was built based on a task analysis from operator interviews and estimates of the probability of operator error. This paper employs a Bayesian approach to assess risks in combine operation. This approach applies a Bayesian Belief Network to agriculture operations, which represents a new application for this risk analysis tool. Sensitivity analysis of different errors and operator skill levels was also performed. The preliminary results indicate that a reduction of human operator action errors can substantially improve the outcomes of the human-machine interaction.

Keywords
risk analaysis, human error, combine operator, harvesting

Disciplines
Bioresource and Agricultural Engineering | Industrial Engineering | Systems Engineering

Comments
This is an accepted manuscript of an article from Proceedings of the Human Factors and Ergonomics Society Annual Meeting 60 (2016): 1414, doi: 10.1177/1541931213601325. Posted with permission.

A Bayesian-Influence Model for Error Probability Analysis of Combine Operations in Harvesting

Yu Du[1], Michael Dorneich[1], Brian Steward[2], Cameron MacKenzie[1]
[1]Industrial and Manufacturing Systems Engineering, Iowa State University
[2]Agricultural and Biosystems Engineering, Iowa State University

Harvesting is one of the most important agricultural operations because it captures the value from the entire cropping season. In modern agriculture, grain harvesting has been mechanized through the combine harvester. A combine harvester enables highly productive crop harvesting. Combine harvesting performance depends on the highly variable skill of combine operators and associated operator error. An approach was developed to analyze the risk of the combine harvesting operation as it relates to operator error. Specifically, a risk analysis model was built based on a task analysis from operator interviews and estimates of the probability of operator error. This paper employs a Bayesian approach to assess risks in combine operation. This approach applies a Bayesian Belief Network to agriculture operations, which represents a new application for this risk analysis tool. Sensitivity analysis of different errors and operator skill levels was also performed. The preliminary results indicate that a reduction of human operator action errors can substantially improve the outcomes of the human-machine interaction.

Keywords: *Risk analysis, Human error, Combine Operator, Harvesting*

INTRODUCTION

Combine harvesting is a common operation in modern agricultural production. Good grain quality and efficient harvesting ensure economic advantages for farmers. However limited literature can be found for assessing risks of combine operations. This paper develops an initial model of the risks for harvesting work using combines harvesters. This analysis identifies major risks and the causes of combine operation, which can be used to assist machine development and improvement, and provide guidance for operation procedures. A risk analysis model was developed for combine operations, which used data collected from expert operators and estimated probabilities to construct a preliminary risk analysis.

Corn is a primary U.S. feed grain with production concentrated in the Midwest region (Capehart, 2015). Soybean is another dominant oilseed crop in the U.S. (Ash, 2016). Given the dominance of these crops, combine harvester observations and operator interviews for combine harvesting operations of corn and soybeans were conducted. The combine harvester is a multi-function harvesting machine that reaps, threshes and winnows grain (Quick, 1978). It is designed for a wide variety of crops such as wheat, oats, rye, barley, corn, sorghum, soybeans, flax, sunflowers, and canola. Compared to traditional, manual harvesting, where reaping, threshing, and winnowing are performed as individual processes, the combine harvester “combines” these processes and thus is a very productive means for harvesting grain. It is also a very complex system that requires high levels of mental concentration for a single operator, which can easily increase the workload and stress level during operation. Human errors may occur because of the complexity and stressful nature of combine operation. Disturbances including radio communication between combine operator and grain cart driver and cell phone conversation may also increase the probability of human operator errors.

Human Error and Risk Analysis

Human error can lead to devastating accidents in aircrafts, ships, and power plants (Johnson, 2007; Acosta, 1993; Pack, 1977). Human errors are often modeled as probabilistic or causal (Rouse, 1983; Acosta, 1983). Probabilistic human errors are errors described by the likelihood of their occurrence, which measures the reliability of humans. Human error analysis iaims to identify the causes of errors. Rouse (1983) introduced different human error categories by focusing on causal situations or finding causes to prevent possible accidents. Rasmussen (1982) defined human performance and errors in actual work situations to better understand the complexity of human errors situations and the data needed to characterize them. He defined three types of human problem solving behavior: skill-based behavior, rule-based behavior, and knowledge-based behavior, and their relation to different error mechanisms.

Risk analysis in human-machine systems should consider the influence of human errors in addition to equipment reliability and the environmental situation (Kirwan, 1992). Various techniques have been developed to characterize human error, including: human error rate prediction (THERP); Hazard and Operability Study (HAZOP); Skill, rule and knowledge-based approach (SRK); systematic human error reduction and perdition method; generic error modelling system (GEMS); potential human error cause analysis (PHECA); and Critical action and decision approach (CADA). Macwan and Mosleh (1994) described a methodology to incorporate operator errors of commission (EOCs) in nuclear power plant probabilistic risk assessments (PRAs). They performed these assessments by taking the appropriate information from the plant PRA operation procedures and the information about the plant configuration. They also combined the risk information with knowledge of the physical and thermal hydraulic system and created performance influencing factors (PIF).

The field of human reliability analysis (HRA) saw further advancements in 21st century. Mosleh and Chang (2004) focused on testing and improving the information decision and action in crew context (ADS-IDAC) model based on a case study. The risk of the wall crack of the reactor pressure vessel in overcooling scenarios were analyzed. The dynamic probabilistic safety assessments (PSA) framework showed promise in their study because the probability of cracking depends on the pressure and temperature of the reactor. They proposed that the ADS-IDAC can support the classical PSA and HRA analysis in the future as well. Trucco (2007) incorporated human and organizational factors (HOF) into a risk analysis of the Maritime Transport System (MTS) and considered different factors such as ship owner, shipyard, and regulators. The Bayesian Belief Network (BBN) model of the MTS was used in this case study to design the stages of high speed ships. A BBN model of HOFs can be used to identify risk mitigation opportunities at the organizational and regulatory level. Trucco's BBN model could be updated over time by using the incident database system and can also support incident reporting or accident investigation.

The topics of human error and risk analysis are often found in the literature in the aviation and nuclear power plant areas. The errors and risks in these areas can have severe negative impacts to human lives and the environment. Kirwan (1992) reviewed and introduced different kinds of methods, which can be used for human error and risk analysis. He also stated that the risk of the whole system cannot be assessed by excluding humans. Most examples found in previous work focused on nuclear power plant control room operation, and aviation (Macwan & Mosleh, 1994). Although the errors and risks for vehicle operation have lower impacts compared to other high impact activities, the large number of vehicle operation activities will result in a high cost of human injury or fatality; thus it is very important to improve machine designs and human machine interactions to reduce risks. Root causes of human errors can determine why operators made these errors. The objective of this work was to develop a risk analysis model of combine operations.

The system-action-management (SAM) framework uses influence diagrams to incorporate human factors into the risks of engineered systems (Murphy, 1996). ABBN predicts the reliability of a complex vehicle system by considering design or process factors through the system life cycle (Neil, 2001).

Methods

Operator Interview and Observation

To assess the error probability of combine operation a thorough understanding of the work is necessary. Operator interviews and observations were conducted to acquire information about the combine harvesting operation. The interview sample size was small, but since the purpose of the paper is to formulate an approach, this size was not of great concern. Guided by an interview protocol, a semi-structured interview was conducted among four interviewees, who had experience operating combines from different brands and with different skill levels. The participants are all male, and their ages range from 25 to 50 years old. Two of them are owner operators and also employed to test equipment. One operator works as a test operator for research purposes and also does a lot of work for customer harvesting. The other operator operates machine mainly for research purpose. They had 9-30 years of experience in operating combines. Their work domain ranged from 323.7 Hectares acres to 3237.5 Hectares, with typical operating durations from two to over ten hours per day. The first fifteen questions asked the interviewees about their working experience, types of operations and equipment. The next fourteen questions asked detailed information about what

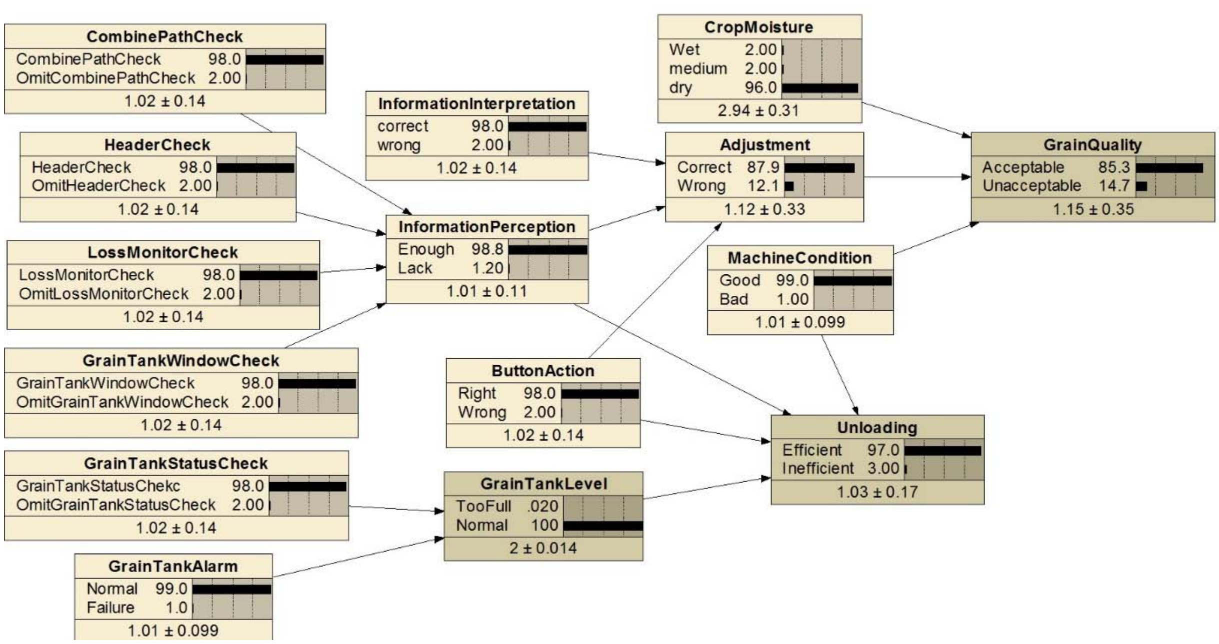

Figure 1. Influence Diagram in Bayesian Belief based Tool

they do during and after operation. Questions included “What kind of information do you want to know before an operation?”, “Can you describe the tasks/steps in the operation, in terms of procedures, tasks, and goals?”, and “How do you know when you are performing well?” Audio recordings and written notes were acquired.

Three ride-along observations were conducted during corn and bean harvest operations. Videos were recorded while the participant operated the machine. Descriptive data and quantitative data were collected, which enable a combination of knowledge-based and entity relationship-based analysis for accurate task analysis (Dix, Finlay, Abowd, & Beale, 2004). The data collected from operator interviews and machine operations were used to understand the operators’ behavior, strategies, and possible risks during the operation, which provided information for risk analysis in the next step.

Risk Analysis Procedure

To analyze the risks and errors of the operation, Bayesian theory was used, which considers the conditional probabilities when describing an event. Two important outcomes from combine operation are grain quality and unloading efficiency. The risk analysis is focused on these two outcomes. Grain quality is measured in terms of the proportions of material other than grain (MOG) and broken and cracked kernels in the grain. Unloading efficiency is the degree the unloading does not slow down the harvesting process. The first step was to define how the operator determined grain quality. The second step was to determine how the operator realized efficient unloading. With these factors being defined, the relationship between operators’ tasks and behaviors and grain quality and unloading efficiency was determined. Operators’ tasks and behaviors were represented by the task model.

A risk model of the operation was developed. The error probability of each task was estimated based on the general knowledge of the combine operation. A Bayesian-based risk analysis model called a Bayesian Belief Net or an influence diagram (Howard, 1984; Pearl, 1988) was created to calculate the probably of poor grain quality and inefficient unloading. Sensitivity analysis was conducted by modifying the probabilities of specific tasks or influences.

Risk Analysis Model

A simplified task analysis was used to develop the risk model. Periodically, the combine operator visually checks the quality of the grain in the grain tank. If the grain has a low level of damage (broken or cracked kernels) and a low proportion of MOG, the grain quality is acceptable. To efficiently unload the grain from the combine harvester into a grain cart towed by a tractor, the unloading should not affect the harvesting rate. Thus it is desirable to unload grain while grain is being harvested, because any time stopped and waiting for the grain cart will lower the field efficiency after the combine grain tank is full. An influence diagram was created with Netica software to assess the probability of unacceptable grain quality and inefficient unloading (Figure 1). Harvested grain quality can be affected by crop moisture, machine condition, and machine adjustment, which can be determined by three factors: information interpretation, information perception, and button actions. Information interpretation represents the operator’s ability to interpret the information perceived. Information perception describes how

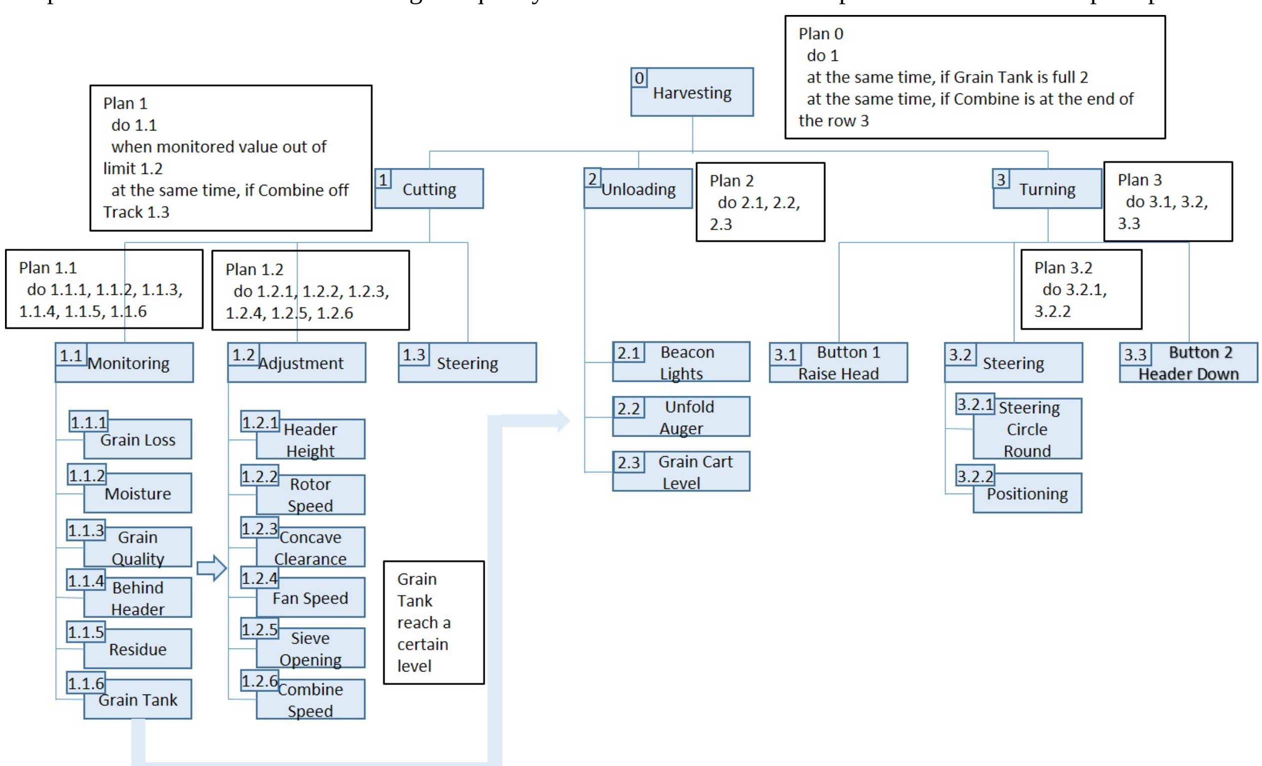

Figure 2. Task Analysis Combine Operation

well the information is perceived by operators. Button action includes the error probability associated with pressing buttons to make adjustments to the machine. The monitoring tasks impact how correctly information is perceived and is one major class of human operator errors in harvesting operations, Efficient unloading, another outcome of the operation, was affected by the machine condition, information perception, button action, and grain tank level. The operator's perception of the grain tank level was impacted by how well they monitored the grain tank status and the grain tank alarm. Normally, if the grain tank reaches a certain level, the grain tank alarm will be triggered to let the operator know that unloading is needed shortly. Probabilities were assessed for all factors in order to calculate the probability of unacceptable grain quality and inefficient unloading (Figure 1).

For one operator during an eight-hour harvesting session, probabilities were estimated for monitoring tasks and button action errors from interviews with the operators and the authors' experience and knowledge gained from the ride-alongs' observations The probabilities for equipment and crop moisture were estimated based on operators' experience. Future studies can undertake more comprehensive data collection effort to better inform the probability model. Validated data can be determined by collecting and analyzing real time data through operation experiments. The model can be simulated with validated error probabilities and be validated by comparing modeling result to collected data.

Seven human operator errors were identified: 1) failure to monitor combine path, 2) failure to check the header check, 3) failure to check loss monitor, 4) failure to check grain tank window, 5) failure to check grain tank status, 6) incorrect information interpretation, and 7) wrong button used for machine control. Crop moisture content and machine condition were classified as influence factors rather than human operator errors.

Results

Task Analysis

Task analysis based on the interviews and observations determined the risk relationship between operation tasks and the outcomes of the combine operation. The risk analysis model was developed based on the task analysis results, illustrated in **Error! Reference source not found.**.

Human operators perceive information about the combine path, header, loss monitor, grain tank window, grain tank status, and grain tank alarm through monitoring tasks. The combine path was monitored to ensure that the combine followed the crop rows with the crop smoothly feeding into the header. Changing crop conditions require the operator to change header settings. The loss monitor would indicate the loss rate during the cutting process. Through the grain tank window, operators visually perceived if the grain quality was acceptable and also determined the level of grain in the tank. The grain tank level monitor sensed if the grain tank was full relative to the grain tank capacity, which then triggered the grain tank alarm. When the operator perceived that the grain tank was full, then they either slowed down harvesting or initiated the unloading process depending on the location of the grain cart relative to the combine. With the correct perception of grain level in the tank and the right human decision, an efficient unloading process was realized. The turning task was initiated at the end of the field.

The operator needs to keep their combine on the right path, ensure the straw and chaff is spread evenly, monitor the quality of the harvested grain, and monitor the level of grain in the grain tank for unloading. Additionally, he or she needs to know whether the crops are fed into the combine header easily and correctly, the amount of corn or beans lost on the field, and the forward machine velocity.

Automation functions such as automatic guidance ease the operators' stress and reduces their workload. Different control layouts and functions exist in different brands and types of combine. The outcome of a system should not be evaluated excluding the equipment and operator. Human errors in combine operation can affect the performance of the harvesting activity and the system. In the following section, risk analysis results are introduced based on the risk model, which was developed based on the understanding of task analysis.

Bayesian Risk Analysis Model

From the BBN (Figure 1), there was a 14.7% probability that grain quality was not within an acceptable range. The probability of inefficient unloading was 3.03%, which means 3.03% of the unloading activities increased the total harvesting time. Sensitivity analysis was conducted to reveal the most important factors for these risks. By estimating the monitoring error probability and button error probability, different expertise levels can be created, which can lead to risk assessment with different expertise levels.

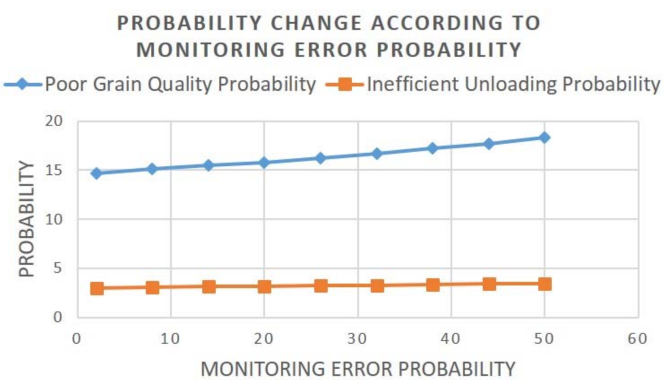

Figure 3. Probability with Increasing Monitoring Error

The error probability of monitoring tasks was increased from 2% to 50% and the button error probability was increased from 2% to 50%. **Error! Reference source not found.** and Figure 4 represent the results of this sensitivity analysis. The monitoring errors can impact the grain quality moderately, but they do not have much impact on unloading. The button error can impact both grain quality and unloading significantly.

Increasing the monitor error probability to 10% and the Button Action Error Probability to 5% may represent a lessexperienced combine operator profile or non-expert. With these new probabilities, the probability of poor grain quality increased to 22.1% and the probability of inefficient unloading increased to 11%. (Table 1).

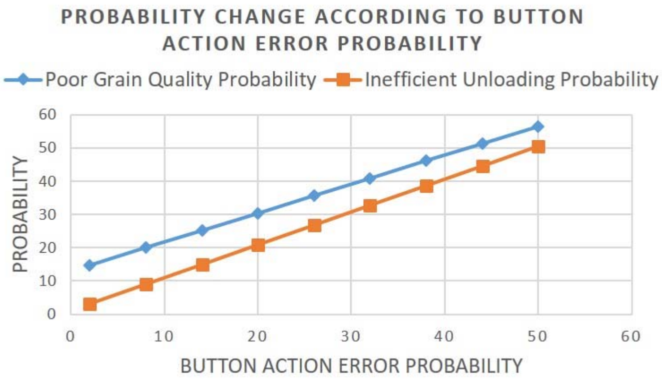

Figure 4. Probability with Increasing Button Action Error

Table 1. Expertise Analysis

Expertise	Monitoring Error Probability (%)	Button Action Error Probability (%)	Poor Grain Quality Probability (%)	Inefficient Unloading Probability (%)
Expert	2	2	14.7	3.0
Non-Expert	10	5	22.1	11

Discussion

The study of scenario in this paper developed a risk analysis approach for combine operation. Based on the risk analysis results, a 50% increase in the monitoring error increase probability resulted in a 3.6% increase in the poor grain quality and a 0.44% increase in the probability of inefficient unloading Compared to monitoring error probability, a 50% increase in the button action error probability increased the bad grain quality 41.8%, and the inefficient unloading probability increased by 47.47%. The button action error affected these two risks more than the monitoring error probability. The results are more sensitive to button action error because 1) the button action error is located in the higher level of the influence diagram, which has a direct influence for unloading and adjustment; and 2) the monitoring signals can compensate for each other in information perception, which means that information perceived from different signals may describe the similar situations. These effects may reduce the impact of monitoring error probability for the risks. To reduce the impact on results due to both button action error probability and monitoring error probability actions and methods can be taken from the human factors perspective following Norman's seven design principles (Dix, 2009) to redesign the interface between man and machine to reduce the button action error probability and monitoring error probability. For example, the layout of the important buttons and the gauge display can be redesigned. By using human factors' methods human-machine interaction can be improved with reduction of error probabilities.

Assessments with different expertise levels reveal how expertise can affect the risks and outcomes of the operation. In general experts tend to have much lower bad grain quality probability and inefficient unloading probability.

For more accurate assessment of the harvesting operation, a detail and complete task analysis should be conducted. Experiments and recording analysis should be conducted for a good quality of data analysis and task analysis. With these analysis monitoring errors and button action error could be predicted in a systematic way by following THERP, HAZOP, or SPK (Kirwan, 1992). Modeling results validation should be performed by using real time operation data collected from experiment. Other factors may also be used for risk analysis e.g. fatigue influence, operator skill levels, and environment condition.

REFERENCES

Acosta, C., & Siu, N. (1993). Dynamic event trees in accident sequence analysis: application to steam generator tube rupture. Reliability Engineering & System Safety, 41(2), 135-154.

Ash, M. (2016, January 5). USDA ERS - Soybeans & Oil Crops: Background. Retrieved from http://www.ers.usda.gov/topics/crops/soybeans-oil-crops/background.aspx

Chess, C., Salomon, K. L., & Hance, B. J. (1995). Managing risk communication agency reality: research priorities. Risk Analysis, 15, 128-136.

Dix, A. (2009). Human-computer interaction (pp. 1327-1331). Springer US.

Howard, R.A. and J.E. Matheson, *Influence Diagrams* in *The Principles and Applications of Decision Analysis*, R.A. Howard and J.E. Matheson, Editors. 1984, Strategic Decisions Group: Menlo Park, CA.

Kirwan, B. (1992). Human error identification in human reliability assessment. Part 1: Overview of approaches. Applied ergonomics, 23(5), 299-318.

Kirwan, B. (1998). Human error identification techniques for risk assessment of high risk systems—Part 1: review and evaluation of techniques. Applied ergonomics, 29(3), 157-177.

Leveson, N. G. (2011). Applying systems thinking to analyze and learn from events. Safety Science, 49(1), 55-64.

Macwan, A., & Mosleh, A. (1994). A methodology for modeling operator errors of commission in probabilistic risk assessment. Reliability Engineering & System Safety, 45(1), 139-157.

Mosleh, A., & Chang, Y. H. (2004). Model-based human reliability analysis: prospects and requirements. Reliability Engineering & System Safety, 83(2), 241-253.

Morgan, M. G., Henrion, M., & Small, M. (1992). Uncertainty: a guide to dealing with uncertainty in quantitative risk and policy analysis. Cambridge University Press.

Murphy, D.M., M.E. Paté-Cornell. "The SAM Framework: Modeling the Effects of Management Factors on Human Behavior in Risk Analysis." *Risk Analysis* 16.4 (1996): 501-515.

Neil, M., Fenton, N., Forey, S., & Harris, R. (2001). "Using Bayesian Belief Networks to Predict the Reliability of Military Vehicles." *Computing & Control Engineering Journal*, 12(1), 11-20.

Pearl, J., *Probabilistic Reasoning in Intelligent Systems: Networks of Plausible Reasoning*. 1988, Morgan Kaufmann Publishers, Los Altos.

Quick, G. R., & Buchele, W. F. (1978). The grain harvesters. American Society of Agricultural Engineers.

Rasmussen, J. (1982). Human errors. A taxonomy for describing human malfunction in industrial installations. Journal of occupational accidents, 4(2), 311-333.

Rassmussen, J. (1986). Information processing and human-machine interaction. An Approach to Cognitive Engineering, Amsterdam, Nom Holland.

Rouse, W. B., & Rouse, S. H. (1983). Analysis and classification of human error. IEEE Systems, Man and Cybernetics, (4), 539-549.

Capehart, T. (2015, November 17). USDA ERS - Corn: Background. Retrieved from http://www.ers.usda.gov/topics/crops/corn/background.aspx

Trucco, P., Cagno, E., Ruggeri, F., & Grande, O. (2008). A Bayesian Belief Network modelling of organizational factors in risk analysis: A case study in maritime transportation. Reliability Engineering & System Safety, 93(6), 845-856.

This is an accepted manuscript of an article from *Proceedings of the Human Factors and Ergonomics Society Annual Meeting* 60 (2016): 1414, doi: 10.1177/1541931213601325. Posted with permission.