18th International Conference on Information Fusion
Washington, DC - July 6-9, 2015

Cognitive and Functional Frameworks for Hard/Soft Fusion for the Condition Monitoring of Aircraft

Joseph T. Bernardo
Applied Research Laboratory (ARL)
The Pennsylvania State University
State College, PA, U.S.A.
jtb17@psu.edu

Abstract–**The synergistic integration of information from electronic sensors and human sources is called hard/soft information fusion. Emerging literature is reviewed according to levels of the Joint Directors of Laboratories data fusion process model. Two frameworks are created for hard/soft information fusion for the condition monitoring of aircraft. First, a cognitive framework is adapted from Orasanu's decision process model and Klein's macrocognition. Second, a functional framework is adapted from the JDL model, and the data-information-knowledge hierarchy is juxtaposed. Levels of inference, machine capabilities, and maintainers' capabilities are also juxtaposed to compare and contrast relative strengths with respect to JDL levels. In ongoing studies, maintainers' information-seeking behavior is observed to make inferences about the cognitive processes underlying their decision-making and its implications for diagnoses, treatments, and resulting outcomes. Improved outcomes and reduced diagnostic effort may reduce operational maintenance cost, increase mission readiness, and increase flight safety.**

Keywords—Hard/soft information fusion, condition-based maintenance, condition monitoring, aircraft maintenance, human factors, decision-making

1 Introduction

The problem of aircraft maintenance and operation involves multiple challenges in understanding and processing sensor data, accessing and applying information from pilots, maintenance personnel, engineers, fleet support teams (FSTs), baseline managers (BLMs), and logisticians. Monitoring the mechanical condition of aircraft is ultimately a critical requirement for the safety of passengers and pilots. While increasing opportunities for advanced sensors are available to support condition monitoring of aircraft, human observations, including assessments of relevant contextual information, appear to be important for success.

Hard/soft information fusion is the synergistic integration of information from electronic sensors and human sources [1]. Numerous advances have been made in the past few years, as follows: i) multi-sensor data fusion, including integrating information from physical "hard" sensors and from human observations "soft" sensors [2], ii) understanding cognitive models for human decision-making and situation awareness [3], and iii) human-centric design of human-computer systems [4]. The current research focused on hard/soft information fusion for decision-making in the context of the condition monitoring of aircraft.

1.1 Literature review

Aircraft maintenance is crucial to flight safety—low-quality maintenance has been a leading factor in aviation accidents, flight delays, and flight diversions [5]. Maintainers face unique stress, knowing the work that they perform today will affect the safety of the crew for years in the future—an emotional burden that is largely unrecognized outside the maintenance community [6].

According to Hobbs, "From a human factors perspective, maintenance personnel have more in common with doctors than with pilots" [6]. Doctors involved in medical treatment may unintentionally cause iatrogenic injury, a threat to patient health induced by the act of treatment [7]. Likewise, the disassembly of aircraft components required for routine inspection and maintenance may unintentionally cause aircraft mechanical problems [6]. Maintenance-induced problems cause almost 15% of commercial aviation accidents [8].

Maintenance of a single civil aircraft used as an air carrier costs an average of $300,000 per year [9]. A single flight cancellation costs an airline $140,000, and flight delays cost an airline $17,000 per hour on average [10]. In the safety-critical domain of aviation, the avoidance of iatrogenic (i.e., maintenance-induced) problems is a strong rationale for condition-based maintenance, which is a maintenance strategy that relies on evidence that indicates the state of deterioration. According to this strategy, the decision to disassemble an aircraft component is based upon evidence rather than a specified time interval (e.g., 1 year) or use interval (e.g., 2000 engine hours).

The hard/soft information fusion literature on condition monitoring is summarized by level of the Joint Directors of Laboratories (JDL) data fusion process model [11].

Galar et al. [12][13][14] and Reiger [15] made no mention of JDL model; however, for the purpose of comparison, all are organized into corresponding levels of the JDL model. The distinction between levels of the JDL model does not imply that levels are decoupled. On the contrary, in real-world information fusion systems, information processing is coordinated across many levels [1].

The hard/soft literature provides little mention of level-0 and level-1 processing, because these levels deal primarily with source pre-processing (e.g., signal and image processing, feature extraction, coordinate transformations) for level 0 and state estimation (e.g., Kalman filtering, feature-based pattern recognition) for level 1. While there are level-0 and level-1 analogs for soft data processing (e.g., text extraction, meta-data generation, image-to-text transformations, etc.), these are not the primary focus of hard/soft information fusion processing.

Level 2/3, human-influenced diagnostics and prognostics, are primarily machine based, but have been enhanced to benefit from some human intervention. Reiger [15] proposed that people be employed to increase the resiliency of automated (i.e., machine-based) diagnostics to unexpected conditions. He studied the identification of abnormal conditions and implications in a control system using automated, distributed reasoning amongst multiple software agents.

Reiger's case studies involve the monitoring of industrial processes: electric power substations, chemical facility reactors, and hazardous facility climate control [15]. The unexpected conditions introduced were sabotage, sensor failure, and equipment failure. The manifestations of unexpected conditions in automated systems create competing goals that are difficult to resolve without human intervention. As shown in Table 1, Reiger posited that systems benefit from improved resilience due to the human cognitive ability to adapt and reason.

Reiger acknowledged that human contribution to resilience could be either beneficial or detrimental. Therefore, he emphasized the importance of training, because "[the] system … will be no better than the proficiency of the least capable individual" [15].

Table 1 – Literature on hard/soft information fusion in condition monitoring organized into levels of the JDL model. Source: Bernardo [11]

Level(s)	Name	Findings
2/3	Human-influenced diagnostics and prognostics [15]	Systems could benefit from improved resilience due to the human cognitive ability to adapt.
2/3/5	Integrated machine- and human-based diagnostics and prognostics [12][13][14]	A more complete assessment of condition led to better diagnostics and prognostics. Safety and reliability were increased, and life-cycle maintenance costs were reduced.
5	Human information processing [4]	Hard/soft information fusion emerges from the interaction between machines and humans.

In levels 2/3/5, integrated machine- and human-based diagnostics and prognostics, functions are shared between machine and human. No single level of the JDL model encompasses integrated machine- and human-based diagnostics and prognostics; instead, such systems are comprised of two components of equal importance. The machine-based component belongs to levels 2 and 3, and the human-based component belongs to level 5. Together, the two components comprise a level-2/3/5, integrated machine- and human-based diagnostics and prognostics fusion system.

In a series of three papers, Galar et al. promoted a hybrid, data-driven, phenomenological approach to fusion in order to aid the condition-based maintenance of railway assets (e.g., locomotives, track components, interchanges) [12][13][14]. In a Machinery Information Management Open System Alliance (MIMOSA) framework, measurements were collected from electronic sensors. Maintainers' notes contain free-text descriptions of faults and actions performed. Each maintainer may describe the same phenomenon differently; therefore, semantic analysis, which is JDL level-0 and level-1 processing for soft data, is essential. Galar et al. reported that awareness of the context mined from the maintainers' notes benefitted diagnostics and prognostics analyses, and it resulted in a more complete, accurate assessment of the condition of railway assets [14]. Safety and reliability of railway assets were increased, and life-cycle maintenance costs were reduced.

Nilsson et al. explored the role of human information processing in level-5 fusion [4]. They proposed the employment of people as active participants in human-machine distributed cognition. They found that hard/soft information fusion emerges from the interaction between machines and humans. Human cognitive processes were identified as fusion resources.

Although Nilsson et al. chose a case study in maritime surveillance [4], the same concepts could be applied to the condition monitoring of aircraft. For example, some aircraft have more than one ground system to aid in diagnostic analyses of aircraft components (e.g., engines, transmissions, and avionics). Using the cognitive functions and processes involved in human information processing, engineers and maintainers could work in cooperation to identify readings, called features, on those ground systems to corroborate the tracking of risks present on the aircraft, even before they become faults.

Previous research has left a gap: the lack of the application of cognitive and functional frameworks to hard/soft information fusion for condition monitoring of aircraft. These frameworks are applied to the domain, and they are informed by other conceptual frameworks.

Cognitive framework

Crandall et al. [16] introduced the concept of macrocognition, and Orasanu [17] developed a decision process model. Cacciabue and Hollnagel said, "Macrocognition is a collection of cognitive functions and processes that describes how people think in the performance of their work in its natural settings" [18]. In the context of aviation maintenance, macrocognition can be viewed as cognitive functions and processes within the aircraft maintainer's mind.

In field studies, Crandall et al. discussed the differences between decision-making in context, and decision-making in an artificially-controlled laboratory environment [16]. They found that mental functions, such as problem detection, which are relevant to aircraft maintenance, occur in the natural context of decision-making. Decisions in the field were often primed by the recognition of the problem situation as something similar to what was experienced in the past. Klein called this recognition-primed decision-making (RPD) [19].

The Orasanu decision process model [17] is a conceptual framework for decision-making strategies. Orasanu drew upon Klein's RPD model [19] and on Wickens and Carswell's information processing model [20]. By adapting the Orasanu decision process model and Klein's macrocognition framework, a cognitive framework is applied to hard/soft information fusion in condition monitoring. In Figure 1, the cognitive framework has been informed by the Orasanu decision process model, Wickens and Carswell's information processing model, and Klein's macrocognition.

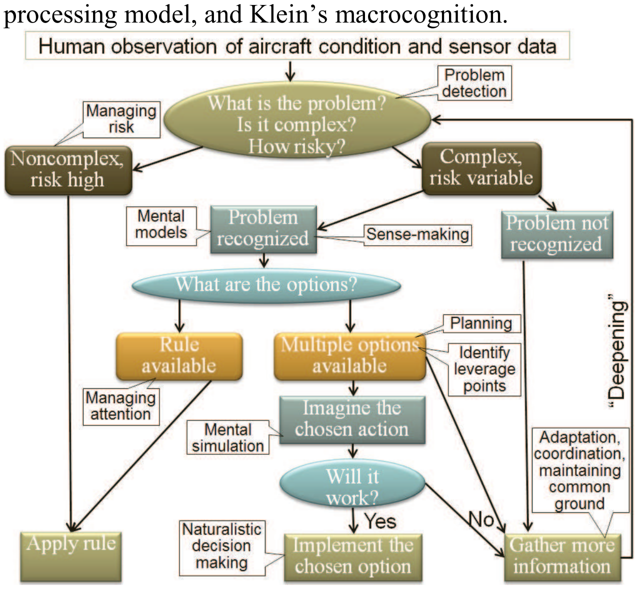

Figure 1 –Cognitive framework for hard/soft information fusion in the condition monitoring of aircraft. Adapted from Orasanu [17]; Klein [19]; Wickens and Carswell [20]; and Crandall, Klein, and Hoffman [16]

Aviation maintenance is safety critical and complex. In selecting a decision-making strategy, maintainers often juggle competing priorities of safety against the organizational unit's mission capability goals (e.g., completing a landing gear inspection during the night before the aircraft's already scheduled dawn mission). One decision-making strategy that maintainers employ is the use of heuristics (i.e., rules of thumb). Time pressure, stress, or both are a rationale for using heuristics for decision-making. Hence, there are differences between "rule available" and "multiple options available."

The functions of macrocognition are sense-making, problem detection, planning, adaptation, coordination, and naturalistic decision-making. The processes constituting macrocognition are managing attention, identifying leverage points, managing risk, performing mental simulations, developing mental models, and maintaining common ground [25]. Faults and human observations regarding an aviation maintenance problem are present at the top level of Figure 1. The maintainer initiates problem detection by asking, "What is the problem?" Then, he or she attempts to manage risk by asking, "How much time is available to fix the problem? How risky is the situation?" Pettersen and Aase found that maintainers balance safety concerns with job-related time pressures [21]. Gill and Shergill cited managing risk as a key factor in the safety practices of aircraft maintenance [22].

The maintainer engages in sense-making and uses mental models in order to recognize the problem. If both rule and multiple options are available, the maintainer has a choice. Does he or she simply apply the rule, perhaps to manage attention, or does he or she evaluate multiple options? Klein et al. found that managing attention was an important process in problem detection [23]. In choosing to evaluate multiple options, the maintainer identifies key leverage points, and engages in planning. Zsambok et al. argued that problem solving is nonlinear and moves forward by identifying leverage points [24]. Orasanu et al. found that most commercial aviation accidents occurred when a compromised flight plan was not replanned [25]. After an option is chosen by the maintainer, he or she engages in mental simulations of each option in order to answer the question, "Will it work?" If the answer is "yes," the maintainer performs the maintenance using naturalistic decision-making [24], which is decision-making in context.

On the other hand, if none of the options are feasible, the maintainer gathers more information in a process called "deepening" by Zsambok and Klein [24]. In deepening, the maintainer is context aware and engages in adaptation. At the same time, he or she maintains common ground and coordinates with flight crew and other maintainers.

2 Functional framework

Since 1988, the JDL model has served as a framework for information fusion research [26]. In 2002, it was revised by Blasch and Plano to consist of six high-level processes [27]. The data-information-knowledge hierarchy was introduced by Cleveland in 1985 [28]. He explained that when data are organized, they are transformed into information, which is raw material for the formation of knowledge.

Figure 2 and Table 2 show the levels of the JDL model using terms that condition-based maintenance professionals in aviation will recognize [11].

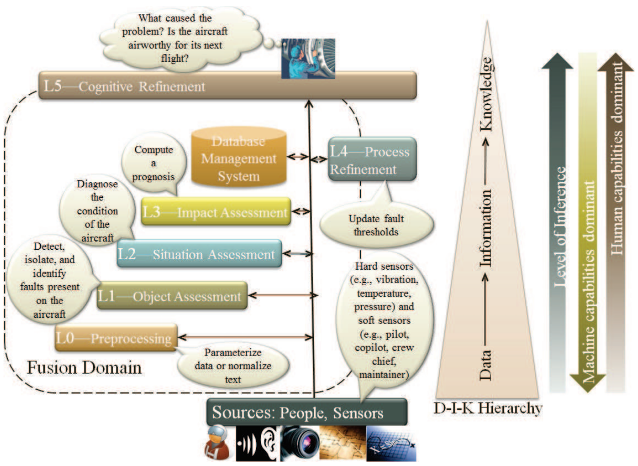

Figure 2 – Functional framework for hard/soft information fusion in the condition monitoring of aircraft. Adapted from Blasch [29] and Hall et al. [30]

Table 2 – The JDL model applied to hard/soft information fusion in the condition monitoring of aircraft. Source: Bernardo [11]

Level, Name	Action	Example/Technique
0 Preprocessing	Parameterize data; normalize text	Reveal harmonics; convert “SWPLT,” “SWPL,” and “SWP” to “swashplate”
1 Object Assessment	Detect, isolate, and identify faults	Apply recognition of flight regime to pattern recognition, trending, and thresholding
2 Situation Assessment	Diagnose the condition of the aircraft	Failure modes and effects analysis (FMEA)
3 Impact Assessment	Compute a prognosis	Failure mode, effects and criticality analysis (FMECA)
4 Process Refinement	Apply MOPs and MOEs	Adjust fault thresholds
5 Cognitive Refinement	Perform decision-making	“What caused the problem? Is the aircraft airworthy for its next flight?”

Level 0 consists of the preprocessing of raw data using signal-processing techniques [31] or of the normalization of descriptive narratives. For example, a fast Fourier transform converts raw signals from accelerometers on a helicopter gearbox into frequency-domain representations to reveal harmonics and other parameters that are used in level-1 analyses [32]. In another example, the abbreviations “SWPLT,” “SWPL,” and “SWP” are all converted to the standard term “swashplate.”

Level 1 integrates sensor parametric data [1] and observations of context. For example, the recognition of flight regime is important in statistical estimation, pattern recognition, trending, and thresholding techniques, which are applied in order to detect, isolate, and identify faults that are present on the aircraft [33].

Level 2 diagnoses the condition of the aircraft by assessing complex mechanical faults, related mission activities, and observations of context [1]. Failure modes and effects analysis (FMEA) form a basis for in-flight troubleshooting procedures.

Level 3 computes a prognosis and assesses impacts [1]. For example, an early identification of single points of failure critical to mission success and safety is performed using Failure mode, effects, and criticality analysis (FMECA). The analysis recommends that engine thrust be limited to 85% until a scheduled retrofit at depot-level maintenance; however, the reduced capability makes the aircraft ineligible for high-altitude or high-gross-weight missions.

Level 4 is a meta-process that regulates other fusion processes, often in accordance with measures of performance (MOPs) and measures of effectiveness (MOEs) [34]. For example, fault thresholds are adjusted to reduce the number false positives.

Level 5 supports effective and efficient proactive decision-making [29]. For example, a maintainer asks, “Is the aircraft airworthy for the next flight?” In response, the system should report values for components that have the least remaining useful life.

Sources are maintainers, aircrew, and electronic sensors; the consumer is the maintainer. The data-information-knowledge hierarchy is juxtaposed to show the progressive creation of information from data and knowledge from information [30]. The level of inference increases as the level of the information fusion increases [1]. According to the human-centered cognitive systems engineering principles [35], machines’ capabilities to perform information fusion are dominant at lower levels of fusion. In contrast, maintainers’ capabilities to perform information fusion are dominant at the higher levels of fusion.

The work of an aviation maintainer involves decision-making in order to select an aircraft component for repair, replacement, fabrication, or calibration; knowledge (i.e., awareness and familiarity gained by experience of situations) of the maintainer as well as information are accessed. The maintainer would utilize a hard/soft information fusion system in order to integrate information with this knowledge. In accordance with the human-centered approach that is a main theme of this research, Hall et al. aptly said, “The utility of the [information] fusion system must be measured by the extent to which it supports effective decision-making” [30].

3 Discussion

Carroll and Johnson said, "Decision-making is a process by which a person … identifies a choice to be made, gathers and evaluates information about alternatives, and selects from among alternatives" [36]. Decision makers often gather information from people. Researchers from a myriad of medical environments, including nursing [37][38], physician practice [39], clinical decision-making [40], and audiology [41], have studied medical professionals' information-seeking behaviors to make inferences about the cognitive processes underlying their decision-making and its implications for diagnoses, treatments, and resulting outcomes.

In nursing, Bucknall found that the nurses' decision-making was strongly influenced by contextual variables, such as time, risk, and resource availability [37]. Carnevali and Thomas demonstrated that task complexity is a factor in the number of cues that nurses found accessible [38]. In physician practice, Eddy argued that ambiguity about a patient's symptoms weakens the links between a patient's true condition and the chosen diagnosis and treatment [39]. Dee and Blazek [42] found that physicians seek input from colleagues because they convey relevant, context-aware information [43]. The impact of these contextual variables on decision-making has implications for improving patient outcomes.

The researchers listed above studied health professionals' information-seeking behavior to make inferences about the cognitive processes underlying their decision-making. A similar research design methodology is valid for studying aviation maintenance, because, as Hobbs said, "From a human factors perspective, maintenance personnel have more in common with doctors than with pilots" [6].

Rationality is a style of behavior in which cost and benefit (a.k.a. utility) are weighed toward the achievement of a goal. The theory of bounded rationality incorporates the influence of the field environment (i.e., context) on cognitive processes related to information seeking and use [44]. According to Simon, decision makers exhibit two cognitive styles: satisficing and optimizing [45]. Satisficers make decisions quickly based upon information that is easy to access. In contrast, optimizers make lengthy, careful decisions only after finding information that is difficult to acquire.

In the cognitive framework (see Figure 1), satisficing maintainers apply rules (i.e., training, experience, or procedures have provided ready-made solutions). For example, "low tire pressure fault" leads to a prescribed maintenance action: inflate the tire. Optimizing maintainers weigh multiple options by seeking additional information. For example, a description of "fuel system fault" may be associated with the following maintenance actions: "replace fuel pressure sensor," "replace fuel filter," "replace fuel pump," and "unknown." The latter set requires a nontrivial decision posed as a choice.

Goals and information are required in order for maintainers to engage in the cognitive processes of decision-making. Diagnosing a fault and choosing to perform a maintenance action requires seeking information and understanding the desired goal. Maintainers of aircraft who are satisficers apply rules using sensor data; in contrast, maintainers who are optimizers evaluate multiple options using electronic data and human observation. Given that assumption, maintainers of aircraft who use only sensor data would apply rules as their decision-making strategy; those who use human observations and sensor data would evaluate multiple options.

In terms of information-seeking behavior, the difference between "rule applied" and "multiple options" is that maintainers who applied a rule did not seek additional information, but maintainers who evaluated multiple options sought additional information. Contextual factors such as complexity influence decision-making [37]. Complexity weakens the links between the diagnosis and the actual condition of the aircraft. Maintainers' information-seeking behavior shows that they confer with aviation professionals (e.g., pilot, copilot, crew chief, other maintainers) because these professionals offer relevant, context-based assessments, which is valuable in disambiguating a complex problem.

Consider the decision–making strategy chosen by maintainers of aircraft. Before selecting another information source, a maintainer must first decide to seek additional information. Covell et al. observed that less than 30% of physicians' information needs toward patient care were ever pursued; therefore, most patients were diagnosed and treated without additional information seeking [46]. Gorman and Helfand demonstrated that the urgency of the problem and the belief in a definitive answer were positive predictors of physicians seeking additional information [47].

3.1 Suggestions for further research

In the author's ongoing research, a large data set is utilized that contains hard data in the form of built-in test codes, and soft data in the form of descriptive and corrective maintenance narratives. Maintainers' information-seeking behaviors are observed to make inferences about the cognitive processes underlying their decision-making and its implications for diagnoses, treatments, and resulting outcomes.

Additionally, the research approach could be utilized to study hard/soft information fusion in other domains where human observations could be added to diagnostic procedures (e.g., medicine, maintenance of ground vehicles).

Furthermore, interactive electronic technical manuals (IETMS) could be enhanced using collaborative filtering (CF), which is a set of data fusion techniques utilized by many recommender systems (e.g., Tapestry [48], GroupLens [49]). Perhaps best known as "Customers Also

Bought," CF has been used successfully by large online retailers (e.g., Amazon) as a way to enhance customers' online shopping experience. Essentially, CF is the process of recognizing patterns of information from multiple sources [50]. CF techniques typically operate over large data sets.

CF techniques could be successfully applied to the domain of aviation maintenance. For example, k-means clustering could be utilized to identify the k most similar diagnostic maintenance actions for a set of human observations and built-in test codes on a particular aircraft variant. The resulting ranked list of the aircraft components could be titled "Maintainers Also Chose."

Furthermore, maintainers' information-seeking behavior could be guided toward statistically better outcomes during the diagnostic process by enhanced IETMS that have analyzed historical maintenance actions corresponding to the aircraft variant undergoing maintenance. For example, "80% of the time, a better outcome occurred when the pilot was asked this additional question."

4 Conclusions

The synergistic integration of information from electronic sensors and human sources is called hard/soft information fusion. In the condition monitoring of aircraft, the addition of the multisensory capability of human cognition to traditional condition monitoring creates a more complete picture of aircraft condition.

Cognitive and functional frameworks were applied to hard/soft information fusion in the condition monitoring of aircraft. The macrocognitive functions and processes of the aviation maintainer aligned with the steps of the cognitive framework. Emerging literature on hard/soft information fusion in condition monitoring was organized into the levels of the JDL model, and the levels were applied to the process functions of aviation maintenance.

The contributions of this research to the area of the study of hard/soft information fusion have been thoroughly discussed, but it would be remiss not to consider the practical applications of these findings, especially to the area of aviation maintenance. The addition of human observations can improve the outcome of aviation maintenance, so the most likely application would be to enhance IETMS by using CF techniques of data fusion.

In ongoing studies, maintainers' information-seeking behaviors are observed to make inferences about the cognitive processes underlying their decision-making and its implications for diagnoses, treatments, and resulting outcomes. Improved outcomes and reduced diagnostic effort may reduce operational maintenance cost, increase mission readiness, and increase flight safety.

References

[1] D. L. Hall and S. A. H. McMullen, *Mathematical techniques in multi-sensor data fusion*. Artech House, 2004.

[2] D. L. Hall and J. M. Jordan, *Human-centered information fusion*. Artech House Publishers, 2010.

[3] N. A. Giacobe, "Measuring the effectiveness of visual analytics and data fusion techniques on situation awareness in cyber-security," Pennsylvania State University, 2013.

[4] M. Nilsson, J. van Laere, T. Susi, and T. Ziemke, "Information fusion in practice: A distributed cognition perspective on the active role of users," *Inf. Fusion*, vol. 13, no. 1, pp. 60–78, 2012.

[5] I. Hampson, A. Junor, and S. Gregson, "Missing in action: aircraft maintenance and the recent 'HRM in the airlines' literature," *Int. J. Hum. Resour. Manag.*, vol. 23, no. 12, pp. 2561–2575, 2012.

[6] A. Hobbs, "An overview of human factors in aviation maintenance," *ATSB Saf. Rep. Aviat. Res. Anal. Rep. AR*, vol. 55, 2008.

[7] L. L. Leape, "Error in medicine," *JAMA-J. Am. Med. Assoc.-US Ed.*, vol. 272, no. 23, pp. 1851–1856, 1994.

[8] H. S. Rashid, C. S. Place, and G. R. Braithwaite, "Investigating the investigations: a retrospective study in the aviation maintenance error causation," *Cogn. Technol. Work*, pp. 1–18, 2011.

[9] C. Adams, "Tracking Down Maintenance Tracking Software," *Aviation Today*, 01-Aug-2008.

[10] Boeing Commercial Airplanes, "Flight Interruption Cost Estimates," *Boeing Minute*, 2008.

[11] J. T. Bernardo, "Application of the JDL data fusion process model to hard/soft information fusion in the condition monitoring of aircraft," in *SPIE Sensing Technology+ Applications*, 2014.

[12] D. Galar, P. Sandborn, U. Kumar, and C.-A. Johansson, "SMART: Integrating Human Safety Risk Assessment with Asset Integrity," in *Advances in Condition Monitoring of Machinery in Non-Stationary Operations*, G. Dalpiaz, R. Rubini, G. D'Elia, M. Cocconcelli, F. Chaari, R. Zimroz, W. Bartelmus, and M. Haddar, Eds. Berlin, Heidelberg: Springer Berlin Heidelberg, 2014, pp. 37–59.

[13] D. Galar, A. GuSTAFSON, B. Tormos, and L. Berges, “Maintenance Decision Making Based On Different Types of Data Fusion,” *Maint. Reliab.*, vol. 14, no. 2, pp. 135–144, 2012.

[14] D. Galar, U. Kumar, R. Villarejo, and C.-A. Johansson, “Hybrid Prognosis for Railway Health Assessment: An Information Fusion Approach for PHM Deployment,” *Chem. Eng.*, vol. 33, 2013.

[15] C. G. Rieger, “Notional examples and benchmark aspects of a resilient control system,” in *Resilient Control Systems (ISRCS), 2010 3rd International Symposium on*, 2010, pp. 64–71.

[16] B. Crandall, G. Klein, and R. R. Hoffman, *Working minds: A practitioner’s guide to cognitive task analysis*. MIT Press, 2006.

[17] J. Orasanu, “Shared problem models and flight crew performance,” *Aviat. Psychol. Pract.*, pp. 255–285, 1994.

[18] J.-M. Hoc, P. C. Cacciabue, and E. Hollnagel, *Expertise and technology*. Lawrence Erlbaum Associates, 1995.

[19] G. A. Klein, “A recognition-primed decision (RPD) model of rapid decision making,” *Decis. Mak. Action Models Methods*, vol. 5, no. 4, pp. 138–147, 1993.

[20] C. D. Wickens and C. M. Carswell, “Information processing,” *Handb. Hum. Factors Ergon.*, vol. 2, pp. 89–122, 1997.

[21] K. A. Pettersen and K. Aase, “Explaining safe work practices in aviation line maintenance,” *Saf. Sci.*, vol. 46, no. 3, pp. 510–519, 2008.

[22] G. K. Gill and G. S. Shergill, “Perceptions of safety management and safety culture in the aviation industry in New Zealand,” *J. Air Transp. Manag.*, vol. 10, no. 4, pp. 231–237, 2004.

[23] G. Klein, R. Pliske, B. Crandall, and D. D. Woods, “Problem detection,” *Cogn. Technol. Work*, vol. 7, no. 1, pp. 14–28, 2005.

[24] C. E. Zsambok and G. A. Klein, *Naturalistic decision making*. Mahwah, N.J.: L. Erlbaum Associates, 1997.

[25] J. Orasanu, U. Fischer, L. K. McDonnell, J. Davison, K. E. Haars, E. Villeda, and C. VanAken, “How do flight crews detect and prevent errors? Findings from a flight simulation study,” in *Proceedings of the human factors and ergonomics society annual meeting*, 1998, vol. 42, pp. 191–195.

[26] J. T. Bernardo, “A methodology for hard/soft information fusion in the condition monitoring of aircraft,” *SPIE Def. Secur. Sens.*, vol. 8756, pp. 701 – 714, May 2013.

[27] E. Blasch and S. Plano, “JDL Level 5 fusion model: user refinement issues and applications in group tracking,” in *SPIE Aerosense*, 2002, vol. 4729, pp. 270–279.

[28] H. Cleveland, “The twilight of hierarchy: Speculations on the global information society,” *Public Adm. Rev.*, pp. 185–195, 1985.

[29] E. Blasch, “Level 5 (User Refinement) issues supporting information fusion management,” in *Information Fusion, 2006 9th International Conference on*, 2006, pp. 1–8.

[30] D. L. Hall, C. S. Hall, and S. A. H. McMullen, “Perspectives on the human side of data fusion: Prospects for improved effectiveness using advanced human-computer interfaces,” in *Handbook of multisensor data fusion: theory and practice*, vol. 22, M. E. Liggins, D. L. Hall, and J. Llinas, Eds. CRC, 2008, pp. 537–548.

[31] A. N. Steinberg, C. L. Bowman, and F. E. White, “Revisions to the JDL data fusion model,” DTIC Document, 1999.

[32] F. White, “A model for data fusion,” in *Proc. 1st National Symposium on Sensor Fusion*, 1988, vol. 2, pp. 149–158.

[33] J. Moubray, *Reliability-centered maintenance*. Industrial Press, 1997.

[34] E. Blasch, P. Valin, and E. Bosse, “Measures of effectiveness for high-level fusion,” in *Information Fusion (FUSION), 2010 13th Conference on*, 2010, pp. 1–8.

[35] R. R. Hoffman, P. J. Feltovich, K. M. Ford, and D. D. Woods, “A rose by any other name... would probably be given an acronym [cognitive systems engineering],” *Intell. Syst. IEEE*, vol. 17, no. 4, pp. 72–80, 2002.

[36] J. S. Carroll and E. J. Johnson, *Decision research: A field guide.* Sage Publications, Inc, 1990.

[37] T. Bucknall, “The clinical landscape of critical care: nurses’ decision-making,” *J. Adv. Nurs.*, vol. 43, no. 3, pp. 310–319, 2003.

[38] D. L. Carnevali, M. D. Thomas, L. T. Godson, and I. A. Waterloo, *Diagnostic reasoning and treatment decision making in nursing*. Philadelphia, Pa., 1993.

[39] D. M. Eddy, “Variations in physician practice: the role of uncertainty,” *Health Aff. (Millwood)*, vol. 3, no. 2, pp. 74–89, 1984.

[40] J. Dowie and A. Elstein, *Professional judgment: A reader in clinical decision making*. Cambridge University Press, 1988.

[41] J. Doyle, “A survey of Australian audiologists' clinical decision-making,” *Aust. J. Audiol.*, vol. 11, no. 2, p. 75, 1989.

[42] C. Dee, “Information needs of the rural physician: A descriptive study,” *Bull. Med. Libr. Assoc.*, vol. 81, no. 3, pp. 259–264, 1993.

[43] G. J. Leckie, K. E. Pettigrew, and C. Sylvain, “Modeling the information seeking of professionals: a general model derived from research on engineers, health care professionals, and lawyers,” *Libr. Q.*, pp. 161–193, 1996.

[44] J. G. March, “Bounded rationality, ambiguity, and the engineering of choice,” *Bell J. Econ.*, pp. 587–608, 1978.

[45] H. A. Simon, “Theories of bounded rationality,” *Decis. Organ.*, vol. 1, pp. 161–176, 1972.

[46] D. G. Covell, G. C. Uman, P. R. Manning, and others, “Information needs in office practice: are they being met?,” *Ann. Intern. Med.*, vol. 103, no. 4, p. 596, 1985.

[47] P. N. Gorman and M. Helfand, “Information Seeking in Primary Care How Physicians Choose Which Clinical Questions to Pursue and Which to Leave Unanswered,” *Med. Decis. Making*, vol. 15, no. 2, pp. 113–119, 1995.

[48] D. Goldberg, D. Nichols, B. M. Oki, and D. Terry, “Using Collaborative Filtering to Weave an Information Tapestry,” *Commun ACM*, vol. 35, no. 12, pp. 61–70, Dec. 1992.

[49] P. Resnick, N. Iacovou, M. Suchak, P. Bergstrom, and J. Riedl, “GroupLens: An Open Architecture for Collaborative Filtering of Netnews,” in *Proceedings of the 1994 ACM Conference on Computer Supported Cooperative Work*, New York, NY, USA, 1994, pp. 175–186.

[50] L. Terveen and W. Hill, “Beyond recommender systems: Helping people help each other,” *HCI New Millenn.*, vol. 1, pp. 487–509, 2001.