Will Artificial Intelligence Do Away with the Need for Air-Safety Investigators?

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In the event of a serious aircraft accident or incident, it is imperative that the "root" causes be identified and evaluated by the air-safety investigators from relevant States, with the objective of minimising the risk of repeated occurrences, as mandated by Article 26 of the Chicago Convention (Abeyratne, 2012). Depending on the complexity and/or severity of an occurrence, the investigation process can last for an extended period, which can provide reputational and financial risks for parties involved, especially when the root cause of an accident is not identified in an accurate timely manner. Additionally, a 2016-2018 audit conducted by the International Civil Aviation Organisation (ICAO), found that 60% percent of Member States had an inadequate investigator training program that had neglected evidence preservation, poor investigative management processes and deficiencies regarding reporting and in particular, safety reporting (Ng et al., 2021). Given the expansive pool of reports already collated by ICAO's E-library of Final Reports (ICAO Annex 13 6.7), and the observable similarities in occurrences, an opportunity arises to exploit the use of artificial intelligence (AI) to interpret the data and emulate the decision-making ability of an air-safety investigator through two branches of AI known as Expert Systems (ES) and Natural Language Processing (NPL) (Ng et al., 2022; Perboli et al., 2021). This paper will examine how recent advances in expert systems, specifically Fuzzy Logic System inference technique, and Natural Language Processing could be implemented to replace the conventional methods for identifying accident causation, and answer the question; Will artificial intelligence do away with the need for air-safety investigators?

In Australia, the Australian Transport Safety Bureau (ATSB) workflow investigation model is adapted from the model recommended by ICAO, Reason's 'Swiss Cheese' Model. The workflow investigation model consists of five hierarchal safety factors: (1) Occurrence Events, (2) Individual Actions, (3) Local Conditions, (4) Risk Controls, and (5) Organisational Factors (Walker & Bills, 2008). Currently, to determine potential safety factors during an investigation, the ATSB workflow investigation model is used in conjunction with AcciMap, a systems-based technique for accident analysis in complex sociotechnical systems. The purpose for incorporating AcciMap as a reasoning workflow is because it demonstrates through blocks, the sequential process in an investigation and has the potential to highlight any information missed. Additionally, only providing evidence and conclusions without reasoning is futile as it cannot be explained or defended, something which is mandated by ICAO for the credibility of air safety investigations (Walker & Bills, 2008).

One way to reduce the time and resources needed in an air safety investigation could be the application of an expert system to determine contributing factors. Expert systems are one of the most common applications for solving "…complex problems by reasoning through bodies of knowledge, represented mainly as if-then rules rather than through conventional procedural code," and are widely considered one of the first forms of successful AI since their inception in the 1970s (Shmelova et al., 2020 p. 4). The general architecture of an ES consists of User-Inference (UI), knowledge base, and inference engine (Ng et al., 2021). The inference engine is what simulates the problem-solving strategy of human experts through a Rule-Based System (RBS) following the if-then rules as mentioned earlier (Ng et al., 2021).

Several solutions to an inference engine exist such as; A Fuzzy Logic System (FLS) that is able to express vagueness and uncertainty based of quantitative and linguistic knowledge through fuzzy sets, Neural Networks (NN) which can imitate human brain behaviour, Adaptive Neuro-Fuzzy Inference System (ANFIS) - a hybrid that incorporates the human reasoning ability of an FLS with the learning capability of an NN and Bayesian Network (BN) - a mathematical model represented graphically (Ng et al., 2021). However, of all the inference techniques available, Fuzzy Logic Systems is currently considered to be the paramount choice for application to an aircraft accident investigation dataset as it can, "…closely match the sequence of events resolution of past occurrence reports," and is easily traceable linguistically, which are both essential for conclusions and evidence/analysis reasoning to be corroborated against investigators findings (Ng et al., 2022).

The authors Ng et al., (2022), have proposed an ES, that incorporates the use of a Fuzzy Logic System inference technique and AcciMaps, with the aim of emulating the analytical reason model conducted by air safety investigators. "This emulation incorporates into the ES the evidence, hypotheses, sequence of events, and findings of contributing factors from past occurrences," (Ng et al., 2022). The proposed FLS inference technique was applied in conjunction with AcciMaps to a case study in order to evaluate the validity of the novel model. The example study centred around a charter flight on a SA227- AC (Metro III) aircraft that suffered power loss in the left engine, resulting in the engine to cease operating entirely. AcciMaps was able to produce key words or phrases from the report from which the user can compare against "… 'current' initial interviewed information 'on the day of the occurrence,'" (Ng et al., 2022). The investigator can then consider each evidence block in selected AcciMaps and whether his/her assessed state either supports or opposes possibilities presented, after which initial inferred contributing factors can be constructed by the inference system (Ng et al., 2022).

The event blocks from a similar occurrence involving a Beech 58 aircraft that suffered fuel exhaustion, are tested for existence and influence in the past accident to match the current occurrence's evidence to infer significant or contributing factors (Ng et al., 2022). However, the ES still requires a hypothesis to be supported, which in this case is missing two pieces of evidence. Thus, contributing factors cannot be fully inferred, but critically, the ES prompts 'clues' or evidence based off past similar evidence for the two missing pieces of evidence suggesting that "… the ES is asking for their existence to assist in establishing findings or contributing factor(s)," (Ng et al., 2022). This demonstration of the application of the proposed ES, establishes how an ES of this nature has the potential to identify and provide clues as to what avenues of inquiry should be scrutinised more thoroughly for potential contributing factors, that otherwise could have been missed i.e. "*Rpt16_23LC_ Pilot uses incorrect fuel assessment quality before take-off at 1st location"* and *"Rpt16_23LC_ Pilot fuel plan uses incorrect fuel content and weight,"* (Ng et al., 2022) (Appendix).

Therefore, in selecting a Fuzzy Logic System technique in conjunction with AcciMaps, Ng et al. (2022) has proposed an ES that satisfies the requirements for an ES system to be measurable, able to prompt further information, traceable to explain how a conclusion was reached, scalable and able to detect trends with confidence. In doing so, this study has highlighted how an Expert System of this nature would be presently able to support the work and conclusions of air-safety investigators, however it could not be considered to fully replace human experts as of today (Ng et al., 2022).

Another challenging area of air-safety investigators work, comprises identifying the role of human factors (HF) in aviation accident causes, which are estimated to have been present in 80% of aircraft accidents (Abeyratne, 2012). Given the inherently complex nature of human factors, it is often a time-consuming process for investigators to identify how HF contributed to an accident. Currently this multifaceted line of inquiry is considered to be expert based, whereby air-safety investigators analyse human factors events against standard accident causality models such as Reason's 'Swiss Cheese' Model or Software-Hardware-Environment-Liveware (SHEL(L)) model, to better understand the complex interactions of human factors within multiple industrial system components in occurrences (Perboli et al., 2021; Walker & Bills, 2008). The evidence gathered from this tedious analysis is then utilised by investigators to draw conclusions and justify recommendations. The issue of time taken to identify contributing human factors in an investigation costs the industry significantly from both a financial and safety perspective. As discussed earlier, the incorporation of AI presents the potential opportunity to not only assist air safety investigators, but also accelerate the investigation process (Perboli et al., 2021).

A study conducted by Perboli et al., (2021), has proposed an interesting application of AI in combination with the SHEL accident causality model to identify the contribution of human factors in aviation accident causes. The branch of AI examined was Natural Language Processing (NPL), a relatively new field, whereby mathematics and linguistics process large quantities of human (natural) language data (Perboli et al., 2021). Prior to this paper, not much research had been published in machine learning for directly identifying HF in accident reports, aside from reports by Hu et al., (2019) where the authors investigated textual indicator extraction tasks. However, the semi-automatic system did not meet the stringent standards for HF identification and thus, can only at best, guide the investigator in his/her analysis (Perboli et al., 2021).

Perboli et al., 2021, presents a solution that follows a Semantic Text Similarity approach, underpinned by a SHEL-based tagged report. Distributional Semantic theory and Vector-Space Model (VSM) was employed to design a system that can "… represent aviation-related sentences in a semantically meaningful way, and then applied it to a direct correlation between phrases containing the same HF," (Perboli et al., 2021). The correlation can then be implemented to increase the knowledge base through a machine-learning algorithm to recognise HF in new sentences. The new processed event is then analysed for similarity against each Human-Factor tagged sentence in the knowledge base and a similarity score is assigned to every HF. The Human Factors scoring the highest are then presented to the user (investigator) for every event, from which the HFs likely contained in the occurrence can be evaluated (Perboli et al., 2021).

The proposed model was then evaluated against 24 real accident/incident reports produced by aviation experts to determine how it could be imbedded into existing processes and critically, the success of the model in identifying the correct human factors in occurrences (Perboli et al., 2021). Against the human expert reports, the application of the methodology estimated a reduction of time needed of at least "…30% compared to the standard methods of human factors identification," and a precision accuracy in tagging the documents with the correct HFs of 86%, thus presenting a compelling argument for the use of Natural Language Processing by air safety investigators (Perboli et al., 2021). In addition to time and costs saved through the employment of Natural Language Processing, innate differences in opinion and biases among human experts would for the most part be removed, in turn bolstering the credibility and integrity of findings in an investigation (Lundberg et al., 2009; Perboli et al., 2021).

It is clear there are overwhelmingly positive implications for using AI to identify air accident causes and in particular, the contributions of HF to an air accident. By reducing the time and resources required for validating air safety investigators work, ES such as the FLS inference technique proposed by Ng et al., (2022) and application of NLP for human factors identification by Perboli et al., (2021) have the ability to not only save the industry money, but improve safety measurably by allowing regulators and companies to address issues sooner. As for whether artificial intelligence has the potential to do away with the need for air safety investigators, the answer is no. The AI systems described in this report, whilst advanced, are not intended to fully replace an investigator and cannot function completely without user input. The systems would also benefit from a larger knowledge base, and have not been researched or tested rigorously enough to meet the high standards required to satisfy air safety investigations on their own merit (Ng et al., 2022; Perboli et al., 2021). Furthermore, identification of the causal factors in investigations is only one area of work undertaken by air-safety investigators.

Possible areas for further study on this topic could include:

- whether the techniques studied have the potential to change investigation classification outcomes and liability (Shmelova et al., 2020),
- multiple criteria decision analysis techniques in the context of air-safety investigations (Stephen & Labib, 2018),
- how artificially intelligent unmanned aerial systems aid investigators in the initial collection and mapping of evidence on reconnaissance missions, (Shmelova et al., 2020)
- how another branch of AI known as Computer Vision (CV) can understand digital images or videos the way a human visual system can do and how that might help air-safety investigators in the early stages of an investigation (Shmelova et al., 2020),
- how the conclusions of investigators finding can be applied through a fuzzy expert system for aviation risk assessment (Hadjimichael, 2009),
- and finally examining the role of augmented reality (AR) in air accident investigation and training (D'Anniballe et al., 2020).

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Word Count including in text referencing but excluding reference list: 2133

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Appendix

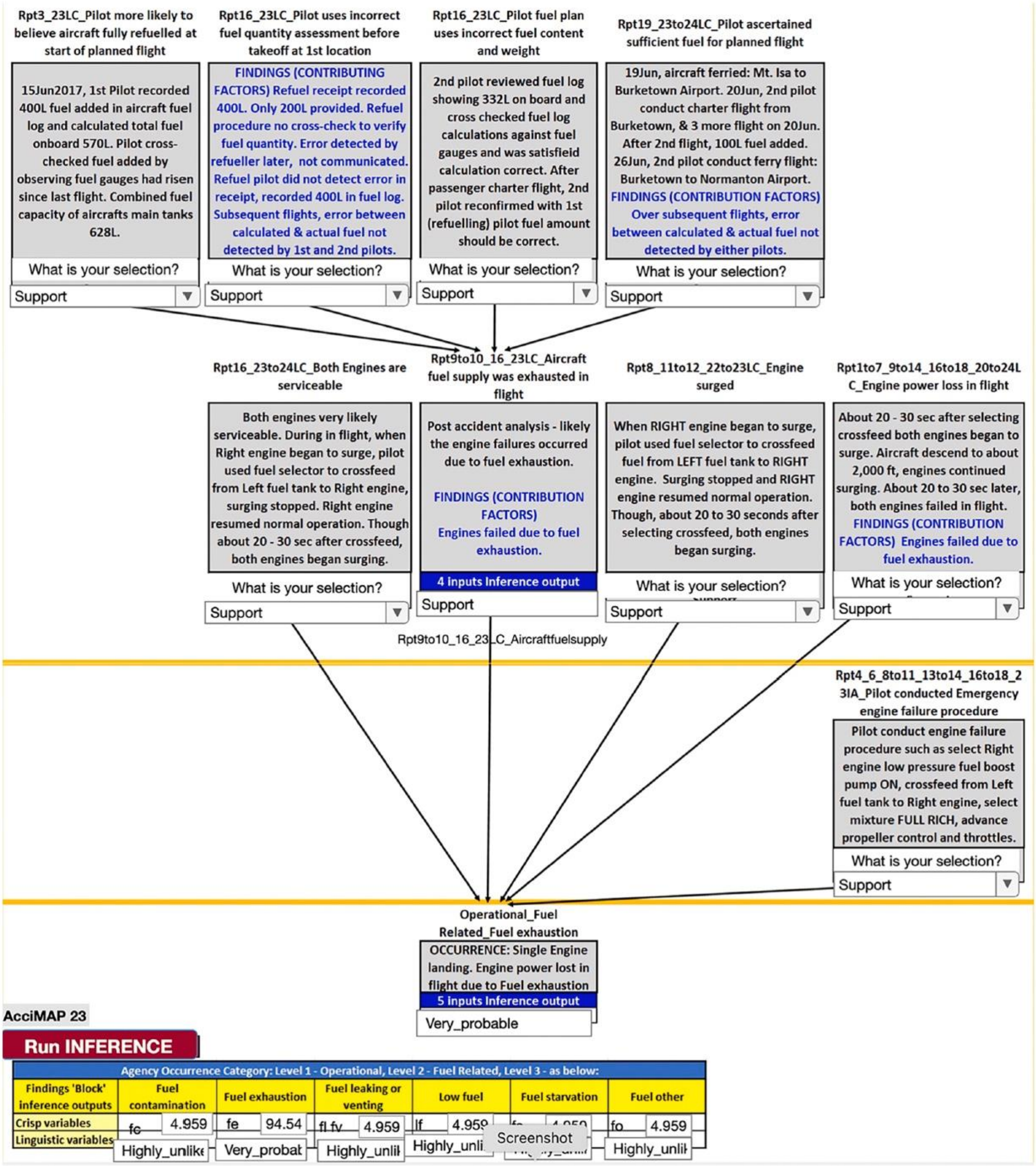

Figure 1: "AcciMap 23 shows the selected 'states' with the additional two pieces of evidence selected as 'Support'. The inference results show that 'Fuel exhaustion: Very probable.'" (Ng et al., 2022)