Modeling General Aviation Startle Causality using Fuzzy Cognitive Maps

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Abstract. Current data in the literature, suggest that over the last decade, loss of control inflight (LOC-I) account for over 40% of all fixed wing fatalities [38]. This issue of LOC is also reflected in UK based data on the subject of General Aviation (GA) accidents causality [23, 48]. As discussed in [24, 32, 38], the occurrence of upsets and LOC have predominantly been studied within the transport and commercial aircraft categories, FAA Title 14 Operations (Parts 121; 135), leaving the GA, Part 91 operations category, a lot less examined and relatively underdeveloped in comparison. This disparity motivates the current research in that, given the propensity of Part 91 rules to be an equally high-risk enterprise, it is worthy of careful consideration regarding LOC-I and upset prevention and recovery (UPR) research. This paper presents an overview of the FCM strategy, applied to the context of startle, their possible causes, and the potential impact on performance, as a holistic approach to understanding and mitigating, the challenge of startle potentiated loss of control.

Keywords: General Aviation Safety, Fuzzy Cognitive Maps, Startle, LOC-I.

1 Introduction

"Aircraft upset" events which have in instances, involved a loss of control in-flight (LOC-I) has been identified as a leading cause of in-line operation fatalities in the last two decades [25]. The LOC incident categorization based on accident and incident analyses over the time period mentioned, has been shown to even surpass the Controlled Flight into Terrain (CFIT) accident category which once topped the accident/incident tables [4, 25]. This drives the current impetus to focus on developing solutions to this issue, particularly in the General Aviation (GA) category (Figure 1). The NTSB in America, suggest in their latest work, that over the last decade, the LOC problem is described to account for over 40% of all fixed wing fatalities [38]. This issue of LOC is also reflected in UK based data on the subject of GA accidents causality [23, 48]; with a key recommendation for improved training to tackle this trend. As discussed in

[3, 5, 23, 24, 38], the occurrence of upsets and LOC have predominantly been studied within the transport aircraft categories, i.e. FAA Title 14 Operations (Parts 121; 135), leaving the GA, Part 91 operations category, a lot less examined and relatively under-developed in comparison. This disparity thus motivates the current research; in that given the propensity of Part 91 operational rules, to be a very high-risk enterprise, just like the commercial category, it is also worthy of careful consideration regarding LOC-I and upset prevention and recovery (UPR) research. The relative affordability of a modern flying experience and the continued push for progress in all things aeronautical safety related, this work proceeds to espouse perspectives which focus on a need, to tackle the LOC; particularly the startle potentiated LOC problem [47], within the context of GA Visual Flying Rules (VFR), Part 91 operations.

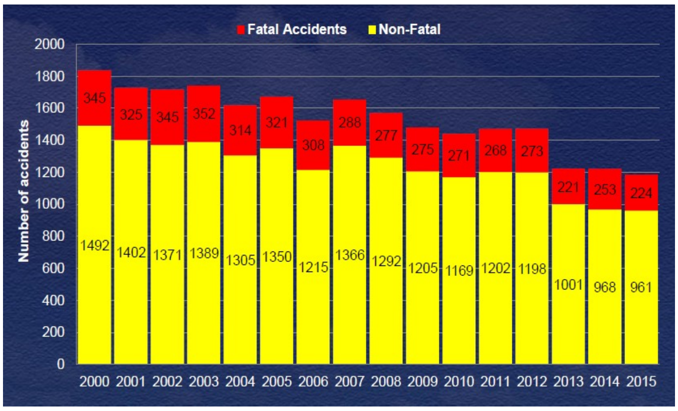


Fig. 1. - General Aviation Accidents [38]

1.1 Aim

We aim to provide an account of human-machine interaction characteristics, in the context of unexpected occurrences, stemming from a pilot in control (PIC), being in a state of startle, or from the loss of situational awareness.

This loss of situational awareness holds immense potential to exacerbate a critical maneouvere, or alter an otherwise benign flight attitude into an upset attitude [6]. We assume a coupling of the human; GA pilot, and the machine; Aircraft, with this position, and this forms the basis upon which the following discussion is presented.

1.2 Objectives

This paper proposes the following objectives towards achieving the aim.

1. To provide an overview of the FCM methodology and apply this to the subject of startle analysis.
2. To develop an FCM framework of startle causality, for the design of an experiment, to investigate and test a startle input to normal flight operations.
3. To provide recommendations on outcomes and for further work in the domain.

1.3 Structure of Paper

The following section of this paper discusses pertinent literature and concepts on the issue of startle causality and the human factors associated with the phenomenon. A brief discussion on the nature of fuzzy set theory is also provided. Section 3 provides details of the FCM framework and the associated codification of the FCM for the current study. Sections 4 and 5 provides conclusions pertaining to the effectiveness of the FCM for representing startle causality and some final thoughts for future work in this regard.

2 Review of Literature

On the subject of startle impacts on performance, current literature suggest that human errors are at the centre of the system dynamics [21, 29, 49]. The HFACS framework, [52] provides an analysis of the error phenomena, aggregating the unsafe acts of operators (i.e. pilots) into two main classifications,

- Errors, which represent the mental or physical inputs which lead to undesirable outcomes.
- Violations, suggesting a disregard for the safety rules which govern flight operations.

To interpret a reasonable abstraction, of startle causality and its underlying dynamics, it is instructive to establish the key factors which drive the startle behaviour, as well as investigate what possible connections exist between them. The following sections provide a discussion on the Fuzzy Cognitive Mapping (FCM) method, for determining startle causality; establishing crucial foundations upon which future experimentation in a simulator are based. The Fuzzy Cognitive Map (FCM), is a method developed by Kosko in 1986 as an extension of cognitive maps, and was originally created using a fuzzy logic viewpoint, for modelling causal knowledge [20, 46] . The map is represented as a diagraph, depicting a specification of concepts as the nodes of a map, and their causal edges, as the strength of each concept's impact to the domain. [40] provides a detailed treatment of this representation. These strengths are represented, as fuzzy weights of any connected concepts in the map. Therefore, outcomes of causality rely on the relationship strength between nodes and define the weight matrix for each iteration of the mapping process.

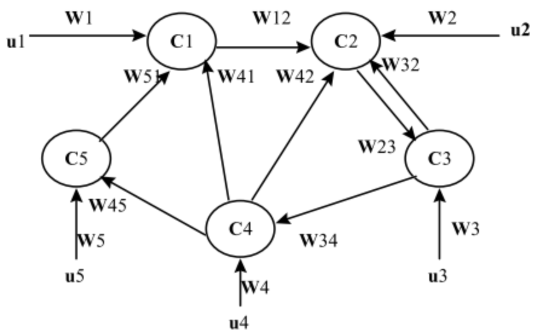


Fig. 2. Diagram of FCM Example [46]

The effectiveness of FCMs can be appreciated, on the basis that behaviours of systems can be studied quite successfully, by combining aspects of fuzzy logic, neural networks, and semantic network theories, in a structured and logical manner, with human expert input helping to form a very rich and useful domain knowledge representation [15, 30, 34]. In the current research, we seek to continue the trend of recent decades ,across various disciplines [2, 19, 20, 39], involving the use of FCMs. However, there is little representation as applied to the topic of startle analysis; more so within the GA arena. This could have wider positive implications with respect to the subject of flight simulation training, and overall pilot safety. To demonstrate the notion of fuzzy logic, in the sense that is applicable to the problem of investigating startle behaviour, consider that traditional logic, typically represents the output of a variable as a binary; True (1), or False (0) outcome. Fuzzy logic on the other hand, represents the value of such variable anywhere between 0 and 1. For instance, the determination of a causal factor of startle in-flight, might be ascribed a value of say, 0.3 or 0.7 to mean partially true or false (i.e. in terms of being impactful to the elicitation of a startle reflex). This value provides an intuitive regard for the relationship strengths between concepts in the FCM. It also provides good foundation for considering causality, in terms of probabilistic thinking on the cause and effect conundrum, where indeterminacy and unpredictability are a mainstay [31]. As a knowledge representation and reasoning technique, the FCM can be used to effectively describe a dynamic system in a form close to how humans perceive it [39, 41, 42]. This characteristic proves to be vital in capturing the experts' knowledge and any other available knowledge from data, in the form of rules emphasizing causal connections and map structure. The resulting fuzzy model is used to analyse, simulate, and test the influence of parameters in order to predict system behavior.

Probabilistic thinking provides a basis, for determination of what level, or degree of truth, is ascribed to causal independent variables. Given a time-critical decision-making situation, such as an unexpected escalating emergency for example, human factors including automation bias, coupled with poor Aeronautical Decision Making (ADM), could force the pilot to maintain reliance on cues emanating from potentially failing sources [7, 8, 52]. Crucially, the perception of the pilot may also be greatly eroded by the unexpected event, further complicating the problem [12]. In such circumstances, it is possible for the startled pilot, to be further hampered by the pressure as per the evolving situation; causing an instinctive reactionary behaviour with a strong potential for a subsequent mishap [26, 29, 43]. The FCM framework provides a methodical way of codifying such.

Assuming that the fluid and complex human decision-making process; during in-flight operations [3, 22], is granted; and can be coupled with the impact of startle on loss of control situations [21, 27, 29], the central principle for studying startle impact on performance is manitained, and the FCM helps to derive a representation, as closely related to reality as possible. The application of an FCM presents a unique opportunity in the domain, to evaluate functional human factors, which are integral in the performance of a flight task, and which may ultimately influence the pilot's reaction to a startling event.

In the literature, various efforts have been made to establish a basis of cognitively modelling and engineering the human factors of decision making and time pressures out of complex processes. Some of the tools which have been documented include the following ACT-R; [14], and MIDAS [17, 50], for instance [18]. These models and frameworks have been extensively studied and documented in the literature but are outside the scope of this submission. However, the FCM framework is deemed to be of greater significance for the present study; Primarily for its ease of use and its wide spread adoption across various disciplines, but significantly this wide spread usage of FCMs is not the case within the aviation domain. This work thus presents the FCM as a viable addition to the study of in-flight human factors pertaining to the startling reactions of a GA pilot. It also provides an easily adaptable and flexible representation method for the uncertainty of modelling a process such as startle causality.

2.1 Fuzzy Sets

The mathematical abstraction of fuzzy logic can be summarized using the logic of fuzzy sets. Consequently; In a crisp set, membership or non-membership of an element, say 'x' in a set A is described by a characteristic function $\mu_A(x)$, where $\mu_A(x) = 1$ if $x \in A$ and $\mu_A(x) = 0$ if $x \in A$. Fuzzy set theory extends this concept further by defining partial membership. This means that a fuzzy set A on a universe of discourse U is characterized by a membership function that takes values in the interval [0, 1]. In essence, this set admits all uncertainties associated with the variable with a graded membership [11].

2.2 FCM Reasoning

For FCM reasoning process, a simple mathematical formulation is usually used. To this end, values of the concept C_i in time t are represented by the state vector $A_i(k)$, and the state of the FCM construct as a whole can be represented by a state vector A(k) = [Ai(k), …, An(k)], which represents a point within what is called a fuzzy hypercube $I^n = [0, 1]^n$. Structurally, an FCM may be represented by what is termed a fuzzy directed digraph with feedback. In this form, it is akin to a collection of neural processing units and weighted relations which could be positive or negative, signifying levels of causality. Using this method, a system could conveniently be demonstrated in terms of the concepts (i.e. variables of the system) and the causal relations between these concepts. Each concept is characterized by its activation degree, which denotes to what extent, a variable is considered active in the system.
There are three possible types of causal relationships between concepts C_i and C_j that express the influence from one concept to another as follows:

- a) $w_{ij} > 0$ indicates a positive causality, then an increase (decrement) on C_i will produce an increment (decrement) on the effect concept C_j with intensity $|w_{ij}|$.
- b) $w_{ij} < 0$ indicates a negative causality, then an increase (decrement) on C_i will produce a decrease (increment) on the effect concept C_j with intensity $|w_{ij}|$.
- c) $w_{ij} = 0$ denotes the absence of a causal relationship between concepts C_i and C_j.

3 Building the FCM

For our case of studying startle events and its association with reduced performance, an event causality FCM serves two functions; explanatory and predictive. This is achieved using a rule-based fuzzy inference system, interpreted from expert opinions. The correlation of causal factors, during the execution of a high cognitive workload, is of key importance to how errors within ADM can be mitigated. This theory allows us to establish a Fuzzy cognitive map (FCM) upon which we can study the issue of a startled pilot. Two questions are considered to this end; would it be possible to determine a concepts (node) hierarchy generation process, based on a consideration of human factors, for a structured analysis of the case study? And from this generation process, does the subsequent aggregated study data provide a logical FCM model representation, to inform the testing of a GA pilot in VFR transitioning to unexpected IFR conditions. To illuminate the degree to which the startled mental model influences the effort of mitigating LOC-I, the flight simulator space provides an environment where these relationships may be tested by pilots, safely and inexpensively. This allows exploration of the hypothesis by the researcher and for the trainee pilot, development of cognitive and motor skills required, to successfully maintain safe operation of aircraft in a startling scenario.

As mentioned, the human factors that are considered within this study and that form the basis of the causal variables used for the questionnaire, are obtained from the HFACS taxonomy on human factors [44]. This work identified 6 major perspectives for the consideration of human factor errors; these include cognitive, ergonomic, behavioural, aeromedical, psychosocial, and organizational perspectives. Based on the application of the SEEV approach for visual attention allocation and performance output analysis; the former being crucial to the task of piloting an aircraft, Figure 3 demonstrates its applicability to the current research in the cognitive, behavioural, and organisational perspectives of task execution driven primarily by the human vision system. However, a full treatment of this framework is outside the scope of this paper. Assurances on the applicability can be taken from [16, 18, 51] in this regard.

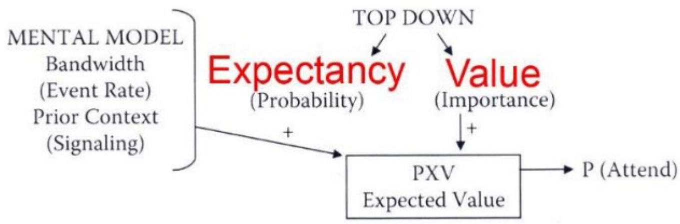


Fig. 3. SEEV Model – Expert Pilot [51]

Provided a normalized weighting of the human factors' variables (causal inputs) can be obtained, the visual comprehension of available information by pilots in a high stressed situation can be examined objectively. [28] provide inspiration from their startle and surprise process as described in figure 1 below. Focusing on the startle aspects specifically, the model is used in conjunction with the Saliency – Effort – Expectancy – Value (SEEV) framework [18, 51] to develop the experiment format, in a way that assesses meta cognitive skills through task performance outputs and pupillometric information capture. The SEEV model provides a way to converge the ideas of cognitive task allocation and execution, based on an expected value of visual scanning or attention allocation. This establishes an understanding of the operator's (Pilot) attention model and supports representation, on key criteria associated with core sub tasks of the "Aviate – Navigate – Communicate" decision making model. Assurances can be taken from These attentional representations are guided by Areas of Interest (AOI); Instrument Panels (IP); Outside World (OW); Cockpit Display of Traffic Information (CDTI), and Bandwidth (BW). Of interest in the present research, are the AOI, IP, and OW. These representations provide a sound foundation upon which the appropriate simulation environment can be developed; as it suggests that eye movements, can provide indications of Pilot in-task attention and as such what is termed as a Stage 1 situational awareness (SA) assessed with the application of eye tracking. Descriptions and other discussions of how eye tracking was also used in this research is currently under development and shall be provided in a future paper. However, the use of such technology here, gives us the opportunity to review the visual acuity of a pilot, in relation to performing a task under unexpected circumstances.

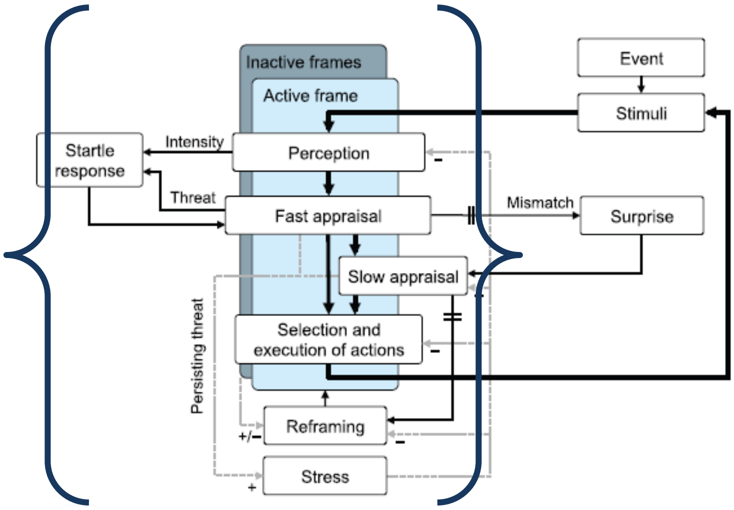


Fig. 4. - Startle - Surprise Process Pathways [27]

The highlighted startle process of Figure 3, allows us to deploy a systematic and fit for purpose experimentation, based on attempting to stimulate a fast response in the active mental frame of the pilot, enough to be considered as “knee jerk”; while forcing a dependency on reframing and managing the elicited stress impact. Using this model, we attempt a goal-based representation of the startle process, via the perception - fast appraisal pathway, leading to the startle reflex being activated. This interaction is investigated in this research for the associated pupillometric features around correct visual processing of indicators for instance (i.e. visual acuity) and the extenuating environmental situations in flight. All of these being achievable through the design of a flight simulation experiment activity around a typical in-flight task in a GA aircraft. Below is an interpretation of the present study highlighting the envisaged route to achieving a startling representation. The principle of this idea aims to decipher said startle through eye tracking data collected when the unexpected stressor event is introduced.

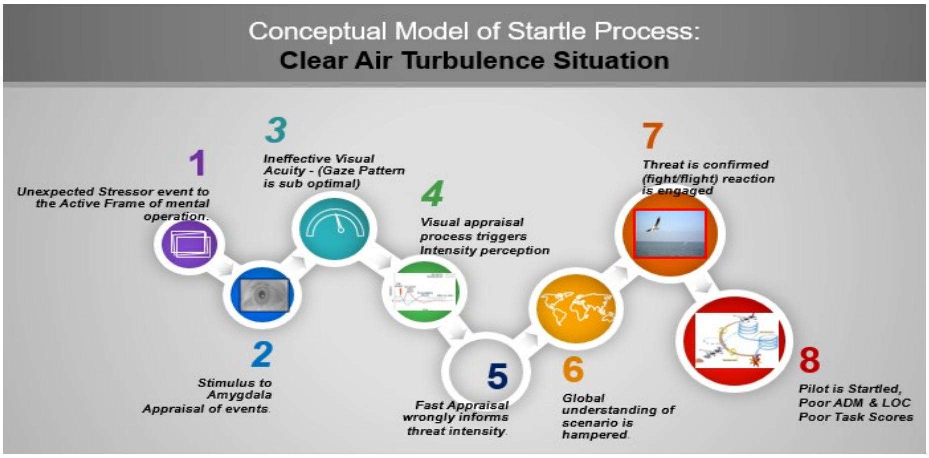


Fig. 5. - GA Startle Process Conceptualisation

In keeping with the research aim, the suggested conceptualisation provides a mental framework for exploring the impact of a startle reaction, in the context of simulated training; and also, a way of contextualising the analysis of task outcomes from pilot actions when startled. The development of the causality factor FCM model is provided in the following sections.

3.1 Codification

For developing the FCM model of a startle, four key principles of expert based construction of FCMs according to [39], is relied upon to populate the map connections. These are as follows:

- Choose the number N and kind of concepts Ci of the FCM – Based on the HFACS framework questionnaire aggregation. The top 5 factors are used for the discussion presented.
- Determine the direction of relationships, and which concept influences another one.
- Use an inference rule to describe the relation between two concepts and infer a linguistic fuzzy set (weight) for the interconnection between the concepts.
- Linguistic weights for every interconnection are combined, defuzzified and transformed in numerical weights.

The following, adopted from the work of [11] provides definitions of a triangular fuzzy number concept, in order to facilitate linguistic variable associations, for the FCM

concepts. The triangulation set of fuzzy numbers, compliment the definitions of the fuzzy variable values (an indication of the expert's judgment) discussed earlier.
The triangulation represents a fuzzy number A denoted by (a_1, a_2, a_3) with a membership function defined as:

$$\mu_{\tilde{A}}(x) = \begin{cases} \dfrac{x - a_1}{a_2 - a_1}, for\ a_1 \leq x \leq a_2 \\ \dfrac{a_3 - x}{a_3 - a_2} j, for\ a_2 \leq x \leq a_3 \\ 0, \quad elsewhere \end{cases}$$

The linguistic variables for the purpose of making judgements on startle causal factors can thus be represented by a value that is a not a crisp number and is associated with comprehensible natural language as the table below shows.

Table 1. - Fuzzy Linguistic Ratings [11]

Linguistic Rating Terminology (Judgement of Influence)	**Triangular Fuzzy Numbers (Numerical rating of factor)**
Very Low Influence	**0, 0, 0.25**
Low Influence	**0, 0.25, 0.50**
Medium	**0.25, 0.50, 0.75**
High Influence	**0.50, 0.75, 1.00**
Very High Influence	**0.75, 1.00, 1.00**

Having been briefed on the basic aspects of what a startle constitutes, in relation to a piloting task, the expert(s) created a fuzzy correlation of the causal factors based on a linguistic representation of causal variables (See Table 2). The FCM structure is driven by a process in which the perception of stakeholders on a certain system (or problem) is uncovered and a representation of the system is thus created. A series of 19 concepts developed on extrapolating the HFACS framework, were deemed relevant to the human factor challenge of startle responses. A complete list of these causal concepts is provided in subsequent outputs. To manage dimensionality of the problem space however, the top 5 causal factors from experts' judgments and rankings, for evoking a startle response, are as depicted in the table below.

Table 2. - Top 5 Causal Factors

Concepts	Causal Factors (Independent Variables)	R1	R2	R3	R4	R5	Ranking Aggregate
C1	Faulty/Uncalibrated Instrument Readings	1	0.75	0.75	1	1	0.90
C2	Appraisal of Evolving Situation	0.75	1	0.75	1	1	0.90
C3	Communication (ATC)	1	0.75	1	0.5	1	0.85
C4	Unskilled Pilot (Not rated for Aircraft Type for instance)	0.75	1	0.75	0.75	0.75	0.80
C5	Insufficient Training/ Lack of Concurrency	0.75	0.75	0.75	0.75	1	0.80

Fig. 6. - GA Pilot – Top 5 Startle Human Factors Causality Chain

3.2 Association

Using the FCM Expert Software tool [35], we are able to create an associative map of the causal concepts. The figure below describes this relationship between the concepts and startle, considered in this case as a cognitive impairment characterized by deficiency in information processing (visual acuity). The simulated parameters include the Kosko's activation function rule with self-memory and a Sigmoid Transfer function [36], for managing the threshold; transformation of the concept at each step. The actual Kosko mathematical representation of FCMs assured by [40] takes the following form:

$$A_i\ (k+1) = f(A_i\ (k) + \Sigma\ A_j\ (k)\cdot e_{ji}) \text{ for j} = 1\ldots\text{N} \tag{1}$$

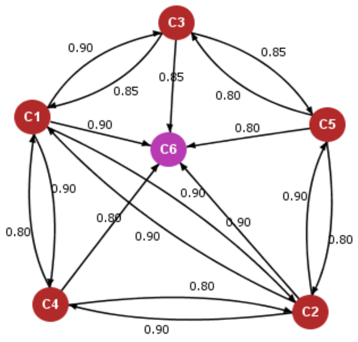
where $f(\cdot)$ is the threshold (activation) function. The equation calculates the values of concepts in the FCM. A Sigmoid threshold function gives values of concepts in the range [0, 1] and has a mathematical representation of:

$$f(x) = 1 / 1 + e^{-\lambda.x} \tag{2}$$

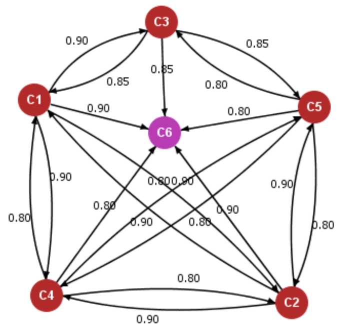
where λ is a real positive number and x is the value $A_i^{(k)}$ on the equilibrium point. In this construct described and implemented in the FCM Expert tool, concepts in the map are activated by making their vector element 1 or 0 ; in the range [0, 1]. The threshold function mentioned earlier, reduces the boundless weighted sum to a predetermined range, allowing for a qualitative comparison between and across concepts, thus representing the fuzzy linguistic associations in the graph. In the literature, there are three main threshold functions namely the Bivalent, Trivalent and the Logistic Signal; a special case; (Sigmoid) functions [30]. The Sigmoid is chosen for the present work as it has been reported to offer significant advantages over the others especially where vision system performances and eye tracking is concerned [10, 39].

The inference process which follows consists of computing the current state vector through time, for a set initial condition [1, 39]. For our case of investigating startle causality, a successive substitution method is preferred, which is implemented by randomly updating the weight matrix of the map using a genetic learning algorithm. This algorithm computes any new state vectors, showing the effect of the activated concept. This occurs through iteratively multiplying the previous state vector by the relational matrix using standard matrix multiplication $A^k = A^{k-1} + (A^{k-1} \cdot W)$. The iteration stops when a limit vector is reached, i.e., when $A^k = A^{k-1}$ or when $A^k – A^{k-1} \leq e$; Where e is a residual, whose value depends on the application type (and in most applications is equal to 0.001) [40]. Thus, a final vector A_f is obtained, where the decision concepts are assessed to clarify the final decision of the specific decision support system.

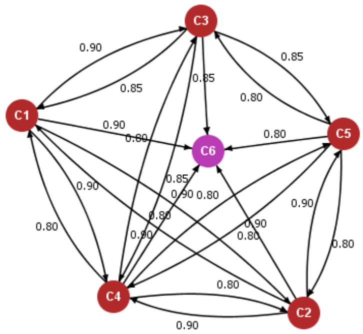
The modification of the weight matrix of the FCM for what-if analysis is made possible using tried and tested learning algorithms [30, 39, 40, 46]. From the existing work on learning algorithms for FCM modelling, there are three main approaches for handling the task of FCM training [13, 39, 45]. These are Hebbian, evolutionary type and a hybrid (of the two) type of learning algorithms. The coverage of these algorithms is extensive in the referenced literature but are beyond the scope of this paper.



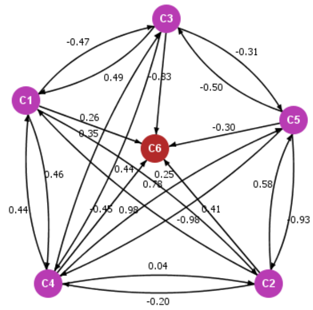
a. Startle is not a decision concept



b. Startle not a decision concept and complex interactions between concepts 1,2, 4, 5

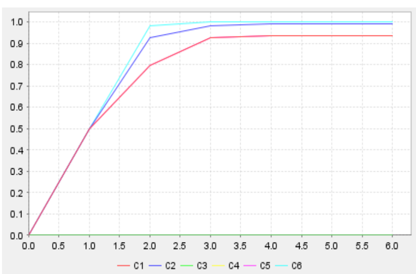


c. Richer Complexity Mapping

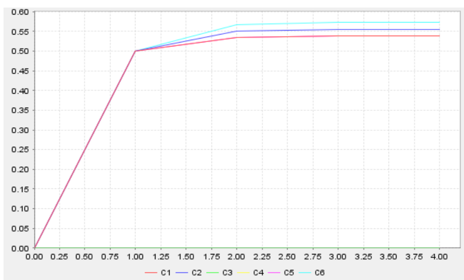


d. Startle considered as only decision concept with randomised weight input from other factors-rescaled

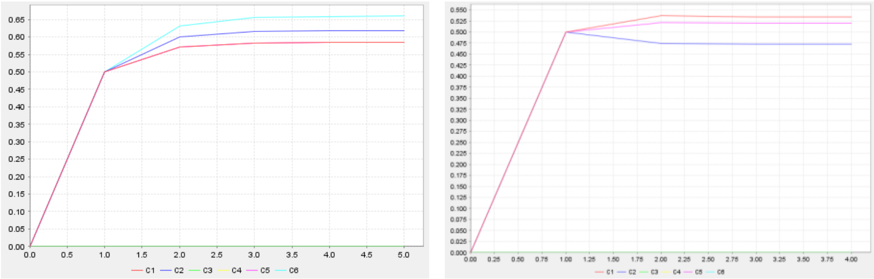
Fig. 7. – FCM Mapping What-If Scenarios



Map a convergence plot



Map b convergence plot



Map c convergence plot *Map d convergence plot*

Fig. 8. - What-If Scenarios; Convergence Plots

The current research adopts the hybrid of these algorithms implemented in the FCM Expert Software [35], combining Hebbian and evolutionary based algorithms in its operation. This enhances the dynamic behaviour and adaptability of the model. What is noteworthy, is that although related in construct to the expert system philosophy, the FCM presents a more flexible framework and possibly a more powerful vehicle for the representation of human knowledge as it moves away from the explicit IF/THEN rules of a traditional expert system. Having developed the map based on input from experts, enumeration of the mapping is achieved using an algorithmic fuzzy protocol that determines the discrete matrix manipulations, necessary between nodes of varying influences interacting in the map.

The successive substitution inference mentioned earlier, indicates the FCM is free to interact and at each interaction step, concepts assume a new value based on the threshold formula and choice of learning algorithm. The present work invokes the Sigmoid function of equation 4 above for this exercise. [36] discusses this in detail and is found to be useful for the development of the research.

4 Conclusions

This paper presented a discussion of the problem space regarding the challenge of startle potentiated loss of control and in-flight operational performance deterioration. It also presents a discussion describing the basis of a conceptual cognitive model, mapping significant relationships between key variables of a simplified “startled” mental model, in the form of a fuzzy cognitive map. Using expert fuzzy judgement inputs, we determine from an abstraction of the HFACS framework the top 5 human factor contributors to the startled process representation in an GA context. These contributors are crucial to understanding the symbiotic framework of our human-aircraft interaction system and help in guiding the development of simulation experiments. The use of an FCM model in this case is grounded on the vision of this work to contribute a fresh perspective into the current discussions in the GA community. Indeed, the goal, is to determine new ways of training and supporting optimal decision making during exigent circumstances, which could progress into a LOC, or, the prompt resolution of a fully developed airplane upset in low or highly degraded vision environments should avoidance become unattainable.

From the logic of the [28, 51] models, and adopting an extrapolation of HFACS [3, 33, 37] we provide a unique simplification map, to conceptualise a startle process path based on the top 5 factors determined; these are depicted in Figure 6. From the what-if scenarios developed (Figure 7 a – d), concepts 1, 2 and 5 consistently emerge as the key factors amongst the 5. Concept 2, i.e. poor situation appraisal, comes out on top in all the scenarios tested as shown in the convergence plots of figure 8 a-d. This provides impetus to design out this factor in Pilot training scenarios. In the same regard, there is potential for the use of modern artificial intelligence (AI) technologies to support the mitigation of such challenges. An experiment has been developed in a simulator environment (See Figures 9 and 10 below), and is the subject of a subsequent paper, examining task execution trends, during "no external input"/standard flight conditions; and with an unexpected "external input", in order to determine startled responses from novice pilots. This experiment focuses on capturing any deterioration of performance from the test scores as well as from the physiological outputs using an eye tracker. The premise driving this experimentation is that, a startled individual is more prone to applying instinctive reactions which might not be suitable in a situation where process and precise application of knowledge, are key to delivering a successful outcome [9].

Fig. 9. Simulation Test Platform for Startle effect experiments

Fig. 10. Head Mounted Eye Tracker capture of Visual Performance during experiment

The FCM implementation, proved its usefulness for the current research within four key functions as discussed in [42]; these are explanatory, predictive, reflective and strategic. In the explanatory context, the FCM Expert tool [35]provides a flexible and robust means to reason out an objective representation and therefore, understanding of the causality conundrum, while highlighting any distortions and limits of the representation being investigated. This goes a long way to solve a crucial issue of automating the construction of weights, enabling a wider and more ad-hoc scenario analysis. The predictive function, as the name suggests, provides a prediction of future decisions, actions and tendencies which justify any new instances of a concept. In the presented work, this describes the prediction of the concept which presents the most risk output by the FCM convergence plots. This prediction function lends itself to the analysis of any experiment results collated based on the FCM. The reflective function of an FCM provides a means of judging the adequacy of a decision profile, while the strategic function can be used to generate a more accurate description of a complex scenario.

5 Final Thoughts and Outlook

Although this research currently ignores time dependent saliency of gaze patterns, considering this notion alongside the framework of the SEEV model, the current research presents a promising route to exploring novel training strategies which foster high levels of adaptability in a GA pilot who might become startled.

On a higher level of abstraction, three key agents are crucial to these studies; these included the Human Mental Model; Particularly in IFR/reduced visual conditions and task complexity, Aircraft Mental Model; Aerodynamic and Stability Behavior as a function of pilot inputs; and the Environment Dynamics; The physical world/Simulated

Environment. These key aspects are necessary considerations, when devising a fuzzy representation of the human factors, which influence the emotive startle reaction, when under pressure. Crucially, the effectiveness of the pilot's visual information processing, in such circumstances can be significantly hampered. Therefore, the present work contributes a fresh perspective to guide the provision of startling scenario training to the fledgling GA pilot. Finally, an added benefit of the FCM software implementation is that it helps to expeditiously adapt and test scenarios which interrogate if the null hypothesis may be refuted or accepted.

References

1. Abraham A (2005) Adaptation of Fuzzy Inference System Using Neural Learning. 53–83. doi: 10.1007/11339366_3
2. Ahmadi S, Yeh C-H, Martin R, Papageorgiou E (2014) An FCM-fuzzy AHP approach to estimating organizational readiness for implementing an ERP system. 20th Am Conf Inf Syst AMCIS 2014 1–11. doi: 10.1007/978-94-007-7853-5_2
3. Ancel E, Shih AT (2012) The Analysis of the Contribution of Human Factors to the In-flight Loss of Control Accidents. 12th AIAA Aviat Technol Oper Conf 1–13
4. Belcastro CM (2010) Validation and Verification of Future Integrated Safety-critical Systems Operating Under Off-nominal Conditions. AIAA Guid Navig Control Conf. doi: 10.2514/6.2010-8143
5. Belcastro CM, Foster J V, Aviation C, Team S, Aeronautics N, Generation N, Operations A, Transportation N, Board S, Oscillation PI, Introduction I, Researcher S, Systems D, Branch C, Researcher S, Branch FD (2019) Aircraft Loss-of-Control Accident Analysis. 1–41
6. Boeing (1998) Aerodynamic Principles of Large-Airplane Upsets. http://www.boeing.com/commercial/aeromagazine/aero_03/textonly/fo01txt.html. Accessed 20 Feb 2014
7. De Boer R, Dekker S (2017) Models of Automation Surprise: Results of a Field Survey in Aviation. Safety 3:20. doi: 10.3390/safety3030020
8. Bruder C, Eißfeldt H, Maschke P, Hasse C (2014) A Model for Future Aviation. Aviat Psychol Appl Hum Factors 4:13–22. doi: 10.1027/2192-0923/a000051
9. Castillo D (2017) Training To Startle. 1
10. Demjén E, Aboši V, Tomori Z (2011) Eye tracking using artificial neural networks for human computer interaction. Physiol Res 60:841–4
11. Devadoss AV, Prabakaran R, Felix A (2018) A Hybrid Scenario FCM with VIKOR Technique for Ranking the Factors. Int J Pure Appl Math 119:233–244
12. Diez M, Boehm-davis D a, Holt RW, Pinney ME, Hansberger JT (2001) Tracking pilot interactions with flight management systems through eye movements. Proc 11th Int Symp Aviat Psychol 1–6

13. Felix G, Nápoles G, Falcon R, Froelich W, Vanhoof K, Bello R (2017) A review on methods and software for fuzzy cognitive maps. Artif Intell Rev 1–31. doi: 10.1007/s10462-017-9575-1
14. Foyle DC, Hooey BL, Byrne MD, Corker KM, Deutsch S, Lebiere C, Leiden K, Wickens CD (2005) Human Performance Models of Pilot Behavior. Proc Hum Factors Ergon Soc Annu Meet 49:1109–1113. doi: 10.1177/154193120504901202
15. Gavalec M, Mls K (2011) Evaluation of Subjective Preferences By Fuzzy Cognitive Maps of Semi-Autonomous Decision Making Systems. Proc Int Symp Anal Hierarchy Process Multicriteria Decis Mak 1–6
16. Gollan B, Ferscha A (2016) SEEV-Effort - Is it Enough to Model Human Attentional Behavior in Public Display Settings. Futur Comput 8–14
17. Gore B, Hooey B, Foyle D (2011) NASA's Use of Human Performance Models for NextGen Concept Development and Evaluations. HumansystemsArcNasaGov
18. Gore BF, Hooey BL, Wickens CD, Scott-Nash S (2009) A computational implementation of a human attention guiding mechanism in MIDAS v5. Lect Notes Comput Sci (including Subser Lect Notes Artif Intell Lect Notes Bioinformatics) 5620 LNCS:237–246. doi: 10.1007/978-3-642-02809-0_26
19. Gray S, Cox L MENTAL MODELER: A tool for environmental planning and research Overview of Mental Modeler 1.1 Concept Mapping Interface 1.2 Matrix Interface 1.3 Scenario Interface 2.0 Introduction to Modeling with Mental Modeler: A step-by-step process 3.0 Example 1: Cre
20. Gray SA, Gray S, Cox LJ, Henly-Shepard S (2013) Mental Modeler: A fuzzy-logic cognitive mapping modeling tool for adaptive environmental management. Proc Annu Hawaii Int Conf Syst Sci 965–973. doi: 10.1109/HICSS.2013.399
21. Harrivel AR, Stephens CL, Milletich RJ, Heinich CM, Last MC, Napoli NJ, Abraham N, Prinzel LJ, Motter MA, Pope AT (2017) Prediction of Cognitive States during Flight Simulation using Multimodal Psychophysiological Sensing. AIAA Inf Syst Infotech @ Aerosp 1–10. doi: 10.2514/6.2017-1135
22. Haslbeck A, Eichinger A, Bengler K (2013) Pilot Decision Making: Modeling Choices in a Go-Around Situation. Proc 17th Int Symp Aviat Psychol 548–553
23. Houston SJ, Walton RO, Conway BA, Houston SJ, Walton RO, Walton R 0 (2012) Analysis of General Aviation Instructional Loss of Control Accidents. J Aviat Educ Res 22. doi: 10.15394/jaaer.2012.1402
24. International Air Transport Association (2015) Loss of Control In-Flight Accident Analysis Report 2010-2014
25. Jacobson SR (2010) Aircraft Loss of Control Causal Factors and Mitigation Challenges
26. Landman A, Groen EL, van Paassen MM (René), Bronkhorst AW, Mulder M (2017) The Influence of Surprise on Upset Recovery Performance in Airline Pilots. Int J Aerosp Psychol 27:2–14. doi: 10.1080/10508414.2017.1365610
27. Landman A, Groen EL, van Paassen MM (René), Bronkhorst AW, Mulder M (2017) Dealing With Unexpected Events on the Flight Deck: A Conceptual

Model of Startle and Surprise. Hum Factors J Hum Factors Ergon Soc 001872081772342. doi: 10.1177/0018720817723428

28. Landman A, Groen EL, van Paassen MM (René), Bronkhorst AW, Mulder M (2017) The Influence of Surprise on Upset Recovery Performance in Airline Pilots. Int J Aerosp Psychol 27:2–14. doi: 10.1080/10508414.2017.1365610
29. Martin WL, Murray PS, Bates PR (2012) The Effects of Startle on Pilots During Critical Events : A Case Study Analysis. Griffith Univ Aerosp Strateg Study Cent 387–394
30. Maya BN de, Kurt RE, Turan O (2018) Application of fuzzy cognitive maps to investigate the contributors of maritime collision accidents. Proc 7th Transp Res Arena TRA 2018, April 16-19, 2018, Vienna, Austria 44
31. Mazlack L (2009) Representing Causality Using Fuzzy Cognitive Maps. Fuzzy Inf Process Soc 2009 … 1–6. doi: 10.1109/NAFIPS.2009.5156434
32. Michales AS (2012) Contributing Factors Among Fatal Loss of Control Accidents in Multiengine Turbine Aircraft. Aviat Technol Grad Student Publ
33. Milburn NJ, Dobbins L, Pounds J, Goldman S (2006) Mining for Information in Accident Data. Tech Reports 11
34. Naderpour M, Lu J, Zhang G (2014) An intelligent situation awareness support system for safety-critical environments. Decis Support Syst 59:325–340. doi: 10.1016/j.dss.2014.01.004
35. Napoles, Gonzalo; Espinoza, Leon, M; Grau I (2017) FCM Expert 1.0.0. 1–18
36. Nápoles G, Concepción L, Falcon R, Bello R, Vanhoof K (2018) On the accuracy-convergence tradeoff in sigmoid fuzzy cognitive maps. IEEE Trans Fuzzy Syst 26:2479–2484. doi: 10.1109/TFUZZ.2017.2768327
37. Naval Safety Center (2015) Department of Defense Human Factors Analysis and Classification System. HFACS Br
38. NTSB (2015) Prevent Loss of Control in Flight in General Aviation
39. Papageorgiou EI (2012) Learning algorithms for fuzzy cognitive maps - A review study. IEEE Trans Syst Man Cybern Part C Appl Rev 42:150–163. doi: 10.1109/TSMCC.2011.2138694
40. Papageorgiou EI (2014) Fuzzy Cognitive Maps for Applied Sciences and Engineering. Springer, Berlin Heidelberg
41. Papageorgiou EI (2014) Learning Algorithms for Fuzzy Cognitive Maps — A Review Study. IEEE Trans Syst Man Cybern Part C Appl Rev 42. doi: 10.1109/TSMCC.2011.2138694
42. Papageorgiou EI, Salmeron JL (2013) A Review of Fuzzy Cognitive Maps Research During the Last Decade. IEEE Trans Fuzzy Syst 21:66–79
43. Rivera J, Talone AB, Boesser CT, Jentsch F, Yeh M (2014) Startle and surprise on the flight deck: Similarities, differences, and prevalence. Proc Hum Factors Ergon Soc 2014–Janua:1047–1051. doi: 10.1177/1541931214581219
44. Shappell S a, Wiegmann D a (2000) The Human Factors Analysis and Classification System – HFACS. Security 19. doi: 10.1177/1062860613491623
45. Stach W, Kurgan L, Pedrycz W, Reformat MZ (2005) Evolutionary Development of Fuzzy Cognitive Maps. 14th IEEE Int Conf Fuzzy Syst 2005

FUZZ ’05 619–624. doi: 10.1109/FUZZY.2005.1452465
46. Stylios CD, Groumpos PP (1999) Mathematical formulation of fuzzy cognitive maps. Proc 7th Mediterr Conf Control Autom 2251–2261
47. Talone AB, Jentsch F (2015) Evaluating Startle , Surprise , and Distraction : an Analysis of Aircraft Incident and Accident Reports. 278–283
48. Taylor A (2014) UK General Aviation Accidents : Increasing Safety Through Improved Training
49. Thackray R (1988) Performance recovery following startle: A laboratory approach to the study of behavioral response to sudden aircraft emergencies
50. Tyler SW, Neukom C, Logan M, Shively J (1998) The midas human performance model. Proc Hum Factors Ergon Soc 42nd Annu Meet 1:320–324. doi: 10.1177/154193129804200329
51. Wickens, Christopher D et al (2003) SEEV Model of Visual Attention Allocation
52. Wiegmann D, Shappell S, Boquet A, Detwiler C, Holcomb K, Faaborg T (2005) Human error and general aviation accidents: A comprehensive, fine-grained analysis using HFACS. Federal Aviation Administration, Office of Aerospace Medicine Technical Report No DOT/FAA/AM-05/24