PERGAMON

Engineering Applications of Artificial Intelligence 12 (1999) 523–541

Engineering Applications of
ARTIFICIAL INTELLIGENCE

www.elsevier.com/locate/engappai

Fuzzy situational tree-networks for intelligent flight support

Ivan Y. Burdun[a,*], Oleg M. Parfentyev[b]

[a]Aerospace Systems Design Laboratory, School of Aerospace Engineering, Georgia Institute of Technology, Atlanta, GA 30332-0150, USA
[b]Siberian Aeronautical Research Institute (SibNIA, Novosibirsk, Russia), 149/209, Kr Valdemara Str, Riga, LV-1013, Latvia

Received 1 March 1997; accepted 1 February 1999

Abstract

The problem of intelligent flight support under complex operational conditions is studied. A 'chain reaction' mechanism of a flight accident is described. An affordable method of flight safety enhancement in advanced aircraft is suggested. This method employs the concept of a hybrid intelligent pilot model, which combines positive anthropomorphic and mathematical properties. A central component of this AI model is a comprehensive knowledge base in the form of fuzzy situational tree-network (FSTN) of flight. A conceptual framework and some algorithmic issues of the method are discussed. Examples of FSTN prototyping are demonstrated. Potential applications include an intelligent pilot-vehicle interface, automatic flight-envelope protection, autonomous (robotic) flight including multiple vehicle systems, resolution of conflicts in close free-flight air space, and others. This paper is addressed to specialists and managers in the sector of applied research into intelligent flight control and flight safety.

Keywords: Flight safety; Complex operational domains; Fuzzy situational trees; Intelligent technologies

1. Introduction

1.1. The problem: flight safety under multi-factor situations

The major problem in flight safety is reportedly 'human error, which is a factor in 60–70% of all aircraft accidents. Other major causes are mechanical problems, which account for roughly 17%, and then weather at about 5%...' (Goldin, 1997). However, flight accident simulations demonstrate (Burdun, 1998) that so-called 'human error' is often not a primary or single factor in accident chain. Rather, this is an indication of other, deep cause-and-effect relationships, which determine the behavior of the 'pilot (automaton)-vehicle-operational environment' system in an emergency. Given a certain *combination* of heterogeneous operational conditions (Fig. 1), an aircraft may inadvertently enter an anomalous sub-domain of flight modes with a small safety margin and insufficient chances of recovery. Under such critical situations, *any* subsequent input may become inadequate or inefficient.

Given an emergency, there is a complementary match of strengths and weaknesses between a pilot and a computer. Humans in general possess strong self-preservation instincts. They are quick learners. Expert operators of complex plants are good at predicting plant dynamics under normal and some abnormal conditions. Human operators are also capable of making efficient decisions based on incomplete or fuzzy information. Pilots can characterize various heterogeneous aspects of a complex flight situation as an integral picture, using a few approximate but robust terms.

On the other hand, computers can retain massive volumes of information in accurate and non-decaying formats. In simulation experiments with mathematical models of flight it is possible to virtually test and evaluate the performance of a flight vehicle under extreme or rare operational conditions, including

* Corresponding author. Tel.: +1-404-894-8055; fax: +1-404-894-6596.
E-mail address: ivan.burdun@mail.ru, ivan.burdun@rambler.ru

0952-1976/99/$ - see front matter
PII: S0952-1976(99)00012-3

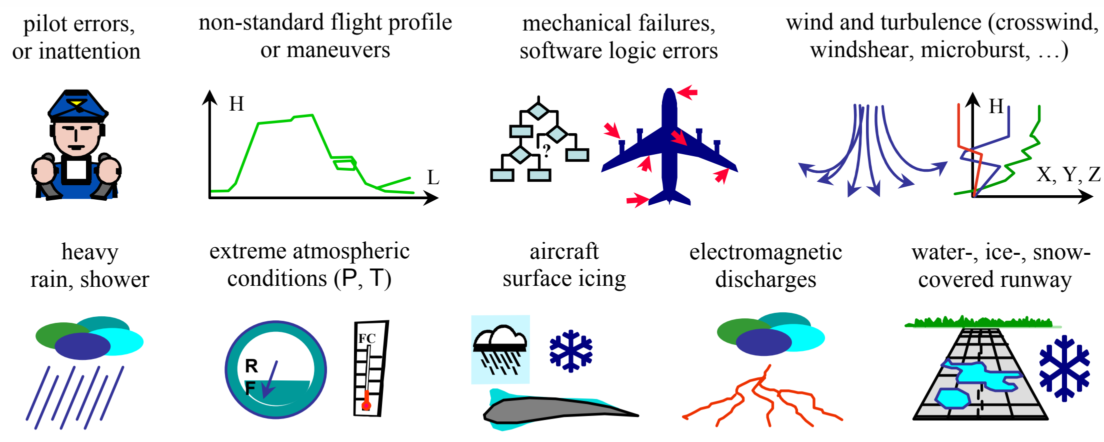


Fig. 1. Main groups of anticipated operational conditions (factors) of flight

unsafe situations. An automatic controller is capable of quick reaction to a detectable abnormal event without panic or procedural errors. Therefore, it would be beneficial to integrate these useful properties of both sides in a single flight safety technology.

1.2. The solution: a knowledge-centred approach

To achieve a higher level of flight safety under complex situations, a *knowledge-centred solution approach* is suggested. The central idea is to combine the positive features of a human pilot's decision-making mechanism with a mathematical modeling and computer simulation of flight. This approach is based on the following two statements:

1. Neither the pilot, nor a computer ultimately controls a flight vehicle. The vehicle is controlled by knowledge, i.e., by the laws of aerodynamics, flight mechanics, and propulsion, etc. The operator (the human pilot, or an automatic control device) acts as a carrier, processor, and/or applicator of these laws.
2. The remedial techniques (i.e., the instructions on how to avoid or rectify a particular emergency) are not new. Normally, the specialists are aware of these techniques *before* the event. However, the challenge is how to derive a subset of knowledge pertinent to the current situation and convey it to the operator before the situation becomes irreversible.

The ultimate *goal* of the knowledge-centred approach is to implement safety as an inherent, 'built-in' feature of a flight vehicle, as its aerodynamics, strength, and comfort are. This, it is suggested, can be achieved by means of *intelligent flight technologies*. These technologies are considered as an extension and integration of the current, human- and computer-centred, approaches to flight automation (Graeber and Billings, 1989; Chatrenet, 1996). Given a complex flight situation, each of the two approaches exhibits shortcomings, which may compromise flight safety. This happens because neither the pilot nor a flight computer possesses enough knowledge of the physics and logic of a complex, multi-factor flight domain. Systematic expertise of this kind is absent in the flight avionics and piloting instructions of modern aircraft.Intelligent flight safety technologies can be implemented by combining the mathematical modeling and computer simulation of flight with the techniques of artificial intelligence. These methods will be used to generate and bring onboard a comprehensive knowledge base of complex system dynamics. A generic flight situation model of flight will be employed as a 'knowledge generator' (Burdun and Mavris, 1997). Through specially planned autonomous computer experiments with the model, systematic knowledge of flight can be accumulated in the form of a fuzzy situational tree-network, or FSTN (Burdun, 1998). The FSTN is basically a synthetic flight experience, or an artificial piloting memory, with an extremely large volume (10^1–10^3 Gbytes) and an open architecture.

The FSTN and its processing functions constitute a *hybrid intelligent pilot model*. The purpose of the model is to predict, during flight, the most likely developments in the current flight situation, 5–25 s ahead, and to identify *critical combinations* of anticipated operational conditions. It will help the pilot to recognize emerging precursors of a 'chain reaction' situation, and to apply physics-based recovery tactics. This AI model is considered as a basis for new technologies for intelligent flight support.

In this paper, a hybrid intelligent pilot model for flight safety applications will be introduced. The focus of the discussion will be on the underlying conceptual framework of the model. Some algorithmic issues are discussed as well. Potential applications are described, using both notional and actual examples.

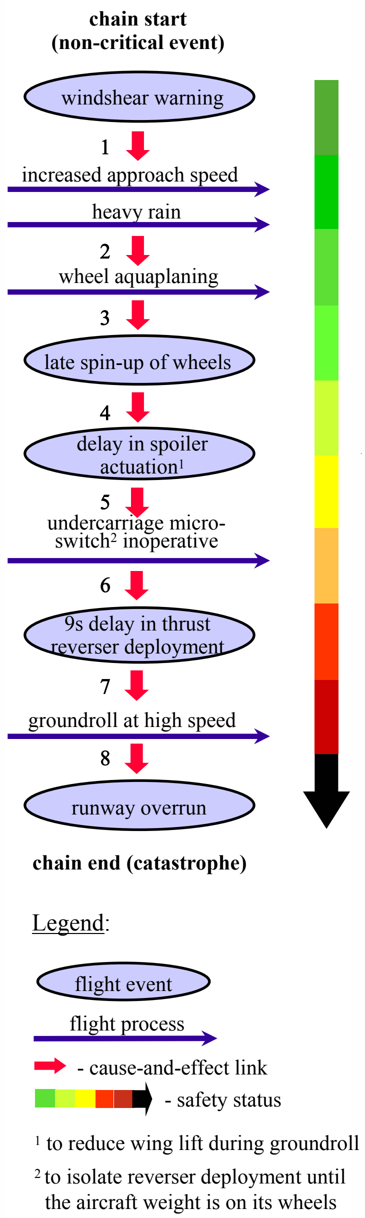


Fig. 2. Chain reaction of a flight accident 'Airplane landing under heavy rain and possible wind shear conditions'.

2. 'Chain reaction' accidents

In this section, the notion of a 'chain reaction' flight accident is discussed. The objective is to demonstrate the necessity of having a comprehensive real-time knowledge base of a complex flight situation domain onboard.

The '*chain reaction*' *of a flight accident* is a complex flight situation, in which several operational factors and their adverse effects are linked by strong cause-and-effect relationships. As the result, flight can quickly propagate towards a catastrophe. Such a situation starts as a relatively safe, non-critical event or process.

'Chain reaction' cases are difficult to correlate with some extraordinary circumstances of flight. Nor can they be addressed to a particular aircraft manufacturer or operator. Another important feature is that these accidents are characteristic of both old and advanced, highly automated vehicles. In fact, over-automation makes modern aircraft even more sensitive to the effect of non-standard flight conditions factors and thus prone to 'chain reactions'. Thus, the *logical mechanism of a 'chain reaction'* has the following general pattern: action of several operational factors, not critically dangerous individually $\Rightarrow$ distortion of a standard profile of flight and control scenario $\Rightarrow$ inadequate control responses from the pilot or an automatic system $\Rightarrow$ a 'snowball' of logical discrepancies in the control scenario $\Rightarrow$ multiple infringements of operational constraints $\Rightarrow$ incident/accident.

2.1. Accident example

Fig. 2 graphically depicts a 'chain reaction' mechanism of a flight accident involving a modern airliner. The aircraft overran the runway and crashed under heavy rain and, possibly, slight wind shear conditions. A rainstorm during approach and landing (performed at an increased airspeed to cope with the wind shear) caused a late spin-up of the wheels after a touchdown due to aquaplaning. A subsequent delay in spoilers deployment (see notes in Fig. 2) caused a 9-s delay in the actuation of the thrust reversers. (Due to a computer-centred design, the pilot was unable to intervene.) As the result, the airplane could not dissipate kinetic energy fast enough within the runway. Note that the flight safety system of the vehicle has contributed to this accident chain (ref. links 4–7 in Fig. 2). In fact, a micro-switch that prevents thrust reverser actuation while *airborne*, has become a trigger of the accident under non-standard *landing* conditions. This micro-switch was installed on this type of aircraft after an accident with an airplane from another manufacturer, due to an uncommanded in-flight deployment of thrust reversers.

2.2. Characteristic properties of 'chain reaction' accidents

This accident demonstrates several important properties of 'chain reaction' flight situations:

- multi-factor chaining character
- 'critical mass' of complexity
- cause-and-effect inertia
- existence of a recovery point
- pilot-automation incoherence.

2.2.1. Multi-factor chaining character

In this case, several internal and external factors are combined: errors in the safety system's logic, heavy rain, a water-covered runway, and possible wind shear. Each of these factors is not regarded as critical on its own. However, as a *complex combination*, they have triggered a very rare, but dangerous, cause-and-effect chain that led to a catastrophe. Therefore, knowledge of multi-factor flight domains is essential for the prevention of such accidents.

2.2.2. 'Critical mass' of complexity

There exists a 'critical mass' of events and processes in a complex flight situation, which may ignite a 'chain reaction' in flight. This 'critical mass' is a function of the number, nomenclature, strength and sequence of the operational factors involved. In flight operations, it is therefore only a matter of time before some critical combination of non-standard conditions triggers such a chain. Therefore, real-time monitoring and identification of critical operational conditions (factors) is also required.

2.2.3. Cause-and-effect inertia

This accident has been literally 'pre-programmed' 10–15 s before the impact. Thus, a capability of near-term prediction of complex system dynamics under key anticipated conditions would be another vital component of advanced flight safety technologies.

2.2.4. Existence of a recovery point

As a result of the previous feature, there exists a 'turning-point' in the course of a critical flight situation. At such a point it is still possible to divert the vehicle safely from a 'chain reaction' flight path by applying, manually or automatically, the correct recovery tactics.

2.2.5. Pilot-automation incoherence

This case also demonstrates that knowledge exchange between the pilot and an automatic system under complex flight conditions is vitally important. The challenge is to make future technologies intelligent, and coherent to both the pilot *and* a computer. Therefore, a two-way process, involving the formalization of the pilot's decision-making processes and an anthropomorphization of the automatic flight control functions, would be beneficial.

2.3. Advanced safety technologies

Thus, this analysis helps formulate the main requirements of advanced safety technologies:

- availability of systematic knowledge of the physics and logic of a multi-factor flight situation domain
- prediction, based on this knowledge, of possible near-term developments of the current situation
- identification, from predicted flight paths, of critical combinations (chains) of operational factors
- prevention of flight from irreversible propagation along critical chains towards a catastrophe, based on a human's self-preservation imperative
- coherent representation and exchange of knowledge relevant to a current situation and its possible developments between the pilot and an automatic system.

3. Situational knowledge of flight

In this section, the notion of situational knowledge of flight will be discussed in conjunction with flight safety.

The *situational* (operational, tactical) *knowledge of flight* may be defined as a system of cause-and-effect, temporal and other relationships, which the operator, the pilot or an automatic system, possesses with respect to various non-standard flight situations, and their transitional dynamics and control. Basically, the operator needs this expertise during flight to obtain answers to the following vital questions:

- What is the current flight situation, and what are its key physical and logical components?
- What are the likely alternatives for near-term development of the current situation? What are the chances of its safe and unsafe outcomes?
- What operational factors will be dominating under possible safe and unsafe developments of flight in, say, 10–25 s?
- Which operational constraint is the nearest one (i.e., the most critical), and how close is the vehicle to it?
- What control inputs should be applied (or avoided), and when, to maintain safe flight?

In the epistemological hierarchy of a pilot's knowledge of flight, the situational knowledge occupies the most important level—between the sensory-motor ('automatic') response skills and the strategic flight mission planning knowledge. Thus, *situational intelligence*, i.e., situational knowledge and the associated processing functions, links together, respectively, the lower (mainly reactive) and the upper (proactive) levels of a pilot's decision-making mechanism. This type of intelligence plays a key role in securing flight safety, as it determines the outcome of a specific maneuver. Therefore, situational decision-making should be the primary target for backup and enhancement by intelligent flight safety technologies.

To enhance situational intelligence of a human pilot, a hybrid AI pilot model is proposed. Basically, the *model's function* is to ensure safe flight at the edge of the flight envelope under two conditions: if the pilot and an automatic control system fail, and if a 'chain reaction' situation is imminent. Therefore, the model's knowledge base (FSTN) is to be much more comprehensive than the pilot's internal model of flight. It should map deep cause-and-effect relationships, which determine the system dynamics in emergencies. This knowledge should cover a multi-factor flight domain, including critical zones at constraints. It should capture a practical spectrum of the most likely non-standard situations based on past flight accident patterns and their 'what-if' derivative situations. Also, this knowledge should be readily available to a pilot and to the flight control computer, in coherent formats.

There are two *main tasks* of intelligent flight support under complex conditions. These are to supply knowledge and to apply it. The *knowledge supply task*, or advisory support to the operator, involves the timely provision of help information (warnings, instructions, prohibitions, explanations, parameter files, etc.) pertinent to a particular emergency. The *knowledge application task* (functional support) involves the performance of the functions of flight control and flight envelope protection for or on behalf of the standard operator under certain conditions. This means partial, temporary or full substitution of the operator if a 'chain reaction' situation is emerging.

4. Flight situation scenario

In this section, the concept of a flight situation scenario is introduced. The flight scenario is the main 'building block' of the knowledge base of a hybrid intelligent pilot model.

4.1. Role of the knowledge model

The role of a correct methodological structure, or knowledge model, in complex systems analyses is crucial. 'After all, complicated tasks usually do inherently require complex algorithms, and this implies a myriad of details. And the details are the jungle in which the devil hides. The only salvation lies in structure.' (Wirth, 1988). Studying the 'pilot-vehicle-operational environment' system dynamics requires an adequate formal framework for representing diverse flight-related knowledge. In the developing approach, this knowledge is modeled at two interrelated levels, called the microstructure and the macrostructure of flight. These structures are described by two interrelated concepts, respectively, the flight situation scenario and the fuzzy situational tree-network of flight.

Basically, objects of four types are sufficient to develop a model of a complex flight situation for computer simulations (Burdun, 1996). These are: flight event, flight process, elementary situation, and flight situation scenario.

4.1.1. Flight event

The *flight event*, $\mathbf{E}$, is a characteristic state of the 'pilot-vehicle-operational environment' system. Flight events are considered as special 'points', or nodes, in a multi-dimensional flight situation space. They are important to the operator in terms of the planning and execution of flight control tactics under a particular situation. Flight events represent discrete components of a flight situation model. Event examples are as follows. $\mathbf{E}_2$: 'on glide slope', $\mathbf{E}_{21}$: 'engine #1 failed', $\mathbf{E}_7$: 'low airspeed', $\mathbf{E}_1$: 'bank angle within 25–30°', $\mathbf{E}_{16}$: 'go-around decision', $\mathbf{E}_9$: 'altitude 1000 ft', $\mathbf{E}_{15}$: 'touchdown', $\mathbf{E}_3$: 'wind shear warning', $\mathbf{E}_{11}$: 'heading 175°'. A complete set of flight events that may occur during a certain phase of flight is called the *flight event calendar*, $\Omega(\mathbf{E})$. The flight event calendar forms a logical framework of a pilot's situational (tactical) decision-making, automatic control algorithms, and a flight situation model itself.

4.1.2. Flight process

Unlike the flight event, the *flight process*, Π_j, is a continuous component of the flight situation model. Its purpose is to represent a distinctive, lasting aspect (action, factor, function, input, operation, etc.) of the system behavior. Depending on the physical nature, processes may be divided into three groups:

- pilot's tactical (situational) decision-making and pilot errors—'*piloting task*' (**T**), system '*state observer*' (**O**), '*control procedure*' (**P**), and some other control processes
- external operational conditions—'*wind*' (**W**), '*rain*' (**R**), '*runway surface condition*' (**Y**), etc., and
- onboard system functions and system failures—'*function*' (**B**) and '*failure*' (**F**).

All the processes planned for a flight situation or a group of situations constitute a *united list of flight processes*, $\Omega(\Pi)$. Examples of flight processes follow. $\mathbf{T}_8$: 'perform a coordinated right turn at a 25° bank'; $\mathbf{O}_6$: 'observe bank angle and roll rate'; $\mathbf{P}_5$: 'flaps—down from 0 to 30°'; $\mathbf{W}_1$: 'strong wind shear, accident *mm/dd/yy*'; $\mathbf{R}_2$: 'tropical shower of a trapezoid profile with the intensity of 300 mm/h'; $\mathbf{Y}_3$: 'wet runway'; $\mathbf{F}_{19}$: 'rudder hardover to +25°'.

4.1.3. Elementary situation

Every process Π in the flight situation runs between two events, the 'source' event and the 'target' event. The *source event*, $\mathbf{E}_*$, opens π, whilst the *target event*, $\mathbf{E}^*$, closes it during flight. An interrelated triplet

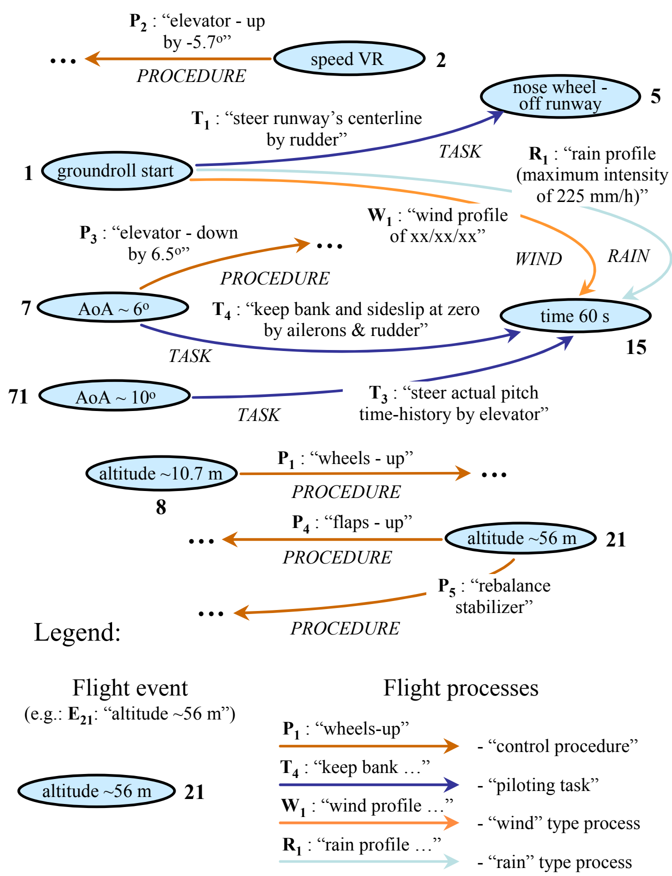


Fig. 3. Flight accident scenario $\mathbf{S}_0$ 'Airliner takeoff under severe microburst conditions'.

s, $\mathbf{s} = (\mathbf{E}_\cdot, \Pi, \mathbf{E}^*)$, is called the *elementary situation*, e.g.: the triplet $(\mathbf{E}_9, \mathbf{T}_8, \mathbf{E}_{11})$.

4.1.4. Flight situation scenario

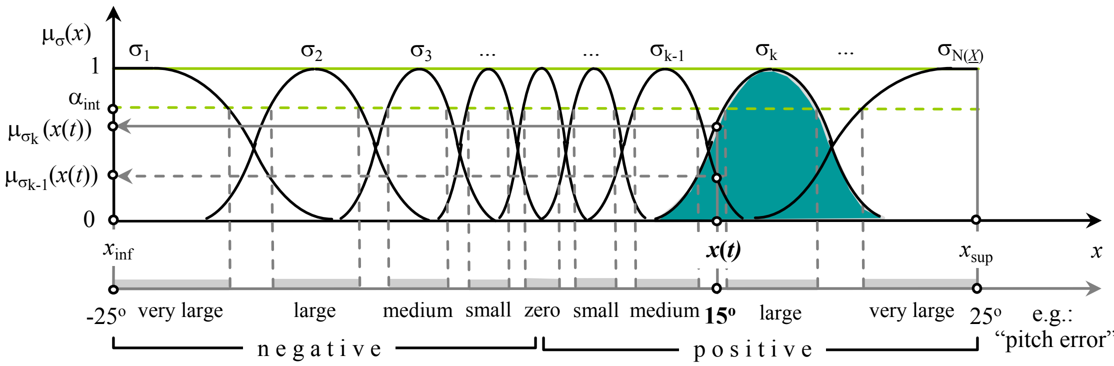
Basically, the *flight situation scenario* (flight scenario) is a plan for implementing some situation and the associated control tactics in flight simulation or operation. It may be visualized as a directed graph $\mathbf{S} = \Omega(\mathbf{E}) \cup \Omega(\Pi)$. Linked together, its vertices $\Omega(\mathbf{E})$ and directed arcs $\Omega(\Pi)$ depict a deep cause-and-effect pattern of a flight situation. Thus, flight scenarios help to visualize and capture complex causal and other key relationships between discrete and continuous elements of a flight situation, thus mapping its invariant logical structure. Note also that a flight scenario may be viewed as a union of its elementary situations.

Fig. 3 depicts a realistic scenario $\mathbf{S}_0$ of a 'chain reaction' flight accident, titled 'Airliner takeoff under severe microburst conditions'. Note that in spite of the complex character of this situation, it is formalized for simulation by only eight events and ten processes. A detailed study of this case, including accident reconstruction and neighborhood analysis, is described in (Burdun, 1998).

4.2. Autonomous flight situation model

The *autonomous flight situation model* is a system of generic algorithms and data structures, which model the behavior of the 'pilot-vehicle-operational environment' system under complex conditions on a computer. Note that human piloting is a part of the model. A formal relationship for executing a flight scenario in simulation experiments with the model is introduced in (Burdun, 1996). This relationship, together with generic models of flight events and processes, constitutes a computational algorithm of the model.

The concepts of a flight scenario and an autonomous flight situation model help one to understand a formal *microstructure of flight*. The majority of actual and hypothetical flight situations (including test modes and accidents) can be planned and simulated on a computer using these concepts (Burdun and Mavris, 1997). Another important feature is that the complex-



$$(\forall x(t))\ (x(t) \in [x_{\inf}; x_{\sup}])\ (\exists \sigma_k)\ (\sigma_k \in \underline{X})\ (\mu_{\sigma_k}(x(t)) = \max \mu_{\sigma_i}(x(t)),\ i = 1, \ldots, N(\underline{X}),\ k \in \{1, \ldots, N(\underline{X})\}) \Rightarrow \underline{x}(t) \cong \sigma_k)$$

Fig. 4. Fuzzy measurement scale of a linguistic flight variable.

ity of the flight scenario planning and simulation tasks does not depend significantly on the complexity of a flight situation under study. Piloting and programming skills are not required.

These concepts were applied to study complex flight situations for 17 aircraft types and three projects of ten manufacturers and design groups. This list includes transport airplanes, helicopters, a tilt-rotor aircraft, and an aerospace vehicle. In total, more than 200 types of flight situation scenarios have been developed, to study over 30 problems in the sectors of aircraft practical aerodynamics, flight control, accident investigation, flight testing, and certification.

5. Fuzzy situation tree-network of flight

In this section, the concept of fuzzy situational tree-network of flight, FSTN, and its components are discussed. The FSTN is suggested as a generic macro-structural model of a complex flight situation domain. It will serve as a knowledge base for a hybrid intelligent pilot model.

Actual flight situations are far from matching the ideal scenarios. This is, perhaps, the most general explanation of aviation accidents and incidents. Due to complex dynamics of the 'pilot-vehicle-operational environment' system, flight, especially under multiple conditions, may deviate from its standard pattern. This happens due to various non-standard conditions (pilot errors, mechanical failures, system's logic errors, demanding weather, etc.) and their combinations, which may affect the normal course of flight at any time. Also, there exist many safe, near-optimal flight trajectories, which however do not fit precisely a standard scenario. Equally, there are numerous flight paths which may bring a vehicle outside the safe envelope, but which are not covered in the vehicle's operational documentation and safety avionics logic.

An actual flight may be represented as a chain of dynamically linked situations (scenarios), which may transition from one to another at any time in the course of a flight. These links vary from flight to flight, and the changes depend on the operational conditions of a particular flight. Thus, a collection of several 'normalized' flights (selected for a specific aircraft type and phase of flight, and presented in comparable data formats and time scales), plotted together, looks like a tree. In this tree, a realization of a standard, ideal flight path forms the trunk, whereas flight paths emerging under non-standard conditions (factors) are depicted by branches.

The modeling and representation of a complex branching domain-tree of flight on a computer is a challenging task. One of the problems is the dimensionality of the system's state space. If system states were described by real-type (numeric) flight variables, computer implementation of the vehicle's state transition matrix would be impossible due to the 'curse of dimensionality' (Zadeh, 1976). Another problem is adequate modeling of the branching logic of a multifactor flight domain, and generic representation of heterogeneous operational factors. Finally, due to the non-linear aerodynamics and strong coupling, the system dynamics at and beyond the constraints may become chaotic and thus very sensitive to contributing factors. This makes the task of complex flight domain analysis even more difficult.

5.1. Components of the fuzzy tree

5.1.1. Linguistic flight variables

To mitigate the negative effects of the first problem, states of the 'pilot-vehicle-operational environment' system in the hybrid pilot model are described by linguistic variables (Zadeh, 1976). Basically, the *linguistic flight variable* measures system states using approximate (fuzzy) values instead of real numbers. Examples of fuzzy values of a linguistic variable 'pitch' are as follows: 'large positive', 'within 3–5°', 'about zero' etc.

5.1.2. Fuzzy measurement scales

Fuzzy values of a linguistic flight variable x are assigned by means of a special 'fuzzy ruler', or fuzzy measurement scale. The *fuzzy measurement scale* (Fig. 4), $\underline{X}$, is a finite ordered set of fuzzy set-values, which can be used to approximately measure 'precise' (numeric) system states. A *fuzzy set-value recognition criterion* implementing a fuzzy mapping $x \rightarrow \underline{x}$ is shown in Fig. 4. Therefore, the variable x is assigned a fuzzy set-value $\underline{x}(t)$, which best fits a corresponding numeric value $x(t)$, based on the criterion from Fig. 4. In aerospace applications, the number of fuzzy set-values in $\underline{X}$ is between 5 and 15. Therefore, the code of a system fuzzy state can be very compact: about 10 times smaller than a code of a numeric state vector of the same length. As the result, it becomes possible to store data on a large flight situation domain efficiently on a computer.

5.1.3. Fuzzy situations

The *fuzzy flight situation*, **S**, is basically a 'fuzzy snapshot' of an actual flight situation. The main attribute of a fuzzy situation is a system fuzzy state. Other attributes include the most recent flight events, ongoing flight processes, and safety and complexity characteristics of the situation (see definitions below). Thus, a fuzzy situation may be considered as an elementary 'cell', or node, in a branching domain-structure of flight-related knowledge.

5.1.4. Fuzzy transitions

A discrete representation of the system evolution from one (*source*) *fuzzy situation* to another (*target*) *fuzzy situation* is called the *fuzzy transition*, **T**. The fuzzy transition integrates physical and logical relationships (cause-and-effect, time, space, instrumental, etc.) between two 'neighboring' fuzzy situations. The information on a fuzzy transition contains codes of new events and processes, which contribute to these relationships, and other attributes.

5.1.5. Fuzzy branches

In AI programming terms, the *fuzzy branch*, **B**, is a chain, or two-way list, of alternating fuzzy situations and fuzzy transitions, which may develop according to some flight scenario or a sequence of such scenarios. In other words, a fuzzy branch is a compact approximate representation of a subset of similar flight paths in the multi-dimensional situational space. Fuzzy situations are depicted as nodes on a branch, and fuzzy transitions are represented as links between 'neighboring' situations. Note that given a fuzzy situation on a branch, it is possible to make forecasts (recalls) and quantitative analyses of future (past) flight paths, which incorporate this situation.

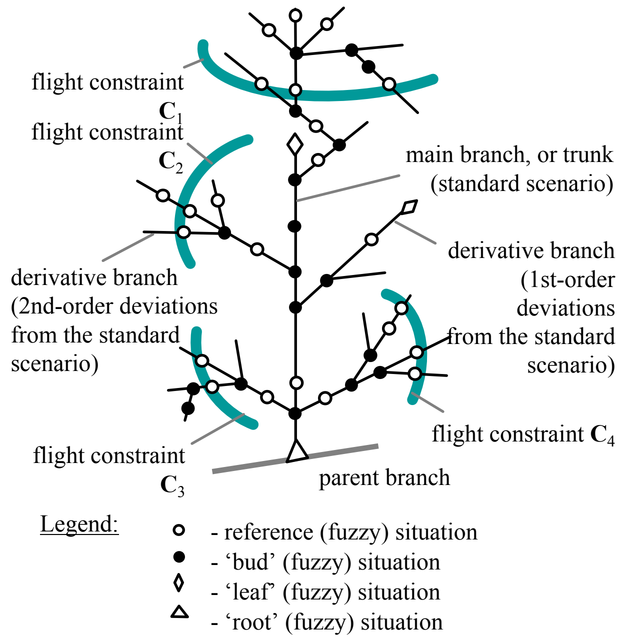


Fig. 5. Fuzzy situational tree-network of flight.

5.2. The fuzzy situational tree-network

In addition to the flight scenario, a more generic knowledge structure is suggested; this is called the *fuzzy situational tree-network, or FSTN* (Fig. 5). The FSTN is an artificial memory, accumulating synthetic experience of many flights in a systematic, structured fashion. It looks like a tree 'planted' in the beginning of some reference flight situation, either standard or non-standard. Within this tree, a new branch emerges from its trunk if the standard flight scenario is no longer being followed. This derivative flight branch may also be called a 'what-if' path, because it is a result of the combined action of demanding operational factors constituting some operational hypothesis. The same principle is applied for implanting higher-order derivative branches into the FSTN.

Thus, the FSTN is a physics-based representation of a complex flight situation domain as a whole. It consists of fuzzy situations and fuzzy transitions, linked into fuzzy branches by cause-and-effect links. The FSTN is constructed as a result of application of various control inputs, which are not necessarily optimal, and anticipated operational hypotheses (see below). A

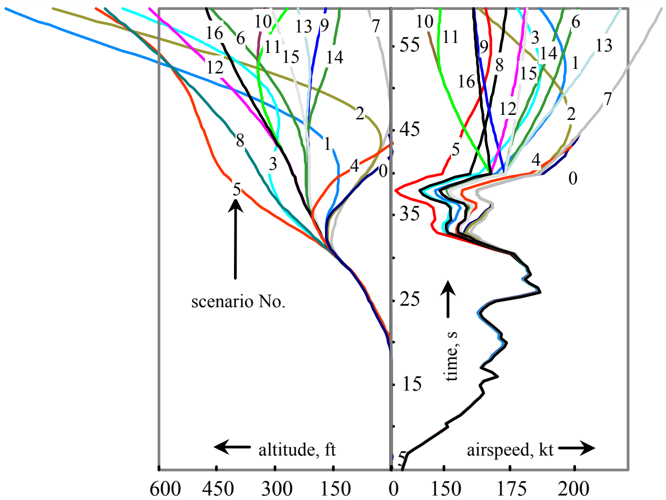


Fig. 6. A basic situational tree of a flight accident and its 'neighborhood'.

crown of the FSTN can be shaped to thread a situational domain under examination, from initially safe states towards constraints. Each branch represents a path that incorporates the effect of an operational hypothesis.

An example of a basic FSTN constructed around the flight accident, the scenario of which is depicted in Fig. 3, is demonstrated in Fig. 6 in the coordinates 'altitude-time' and 'airspeed-time'. This tree incorporates the accident reconstruction scenario $\mathbf{S}_0$ and 16 alternative ('what-if') scenarios $\mathbf{S}_1$–$\mathbf{S}_{16}$; see (Burdun 1998) for more detail.

The FSTN is intended to serve as a real-time knowledge backup for a human pilot or automatic system under demanding conditions, including novel situations. It can be specially designed to reveal unsafe, 'chain reaction' zones in a complex flight domain. Given a subset of key operational hypotheses and a current fuzzy branch, it is possible to explore a subtree of the flight paths that are possible under these anticipated conditions. The goal of this process is to thread a multi-factor flight domain, and reveal zones of possible 'chain reaction' situations based on the physics of flight. This artificial knowledge memory represents 'synthetic flight experience', which can be as many as 10^2–10^3 times more comprehensive than the equivalent tactical (situational) experience of a test pilot under similar conditions.

The concepts of the flight situation scenario and the fuzzy situational tree-network are closely interrelated.

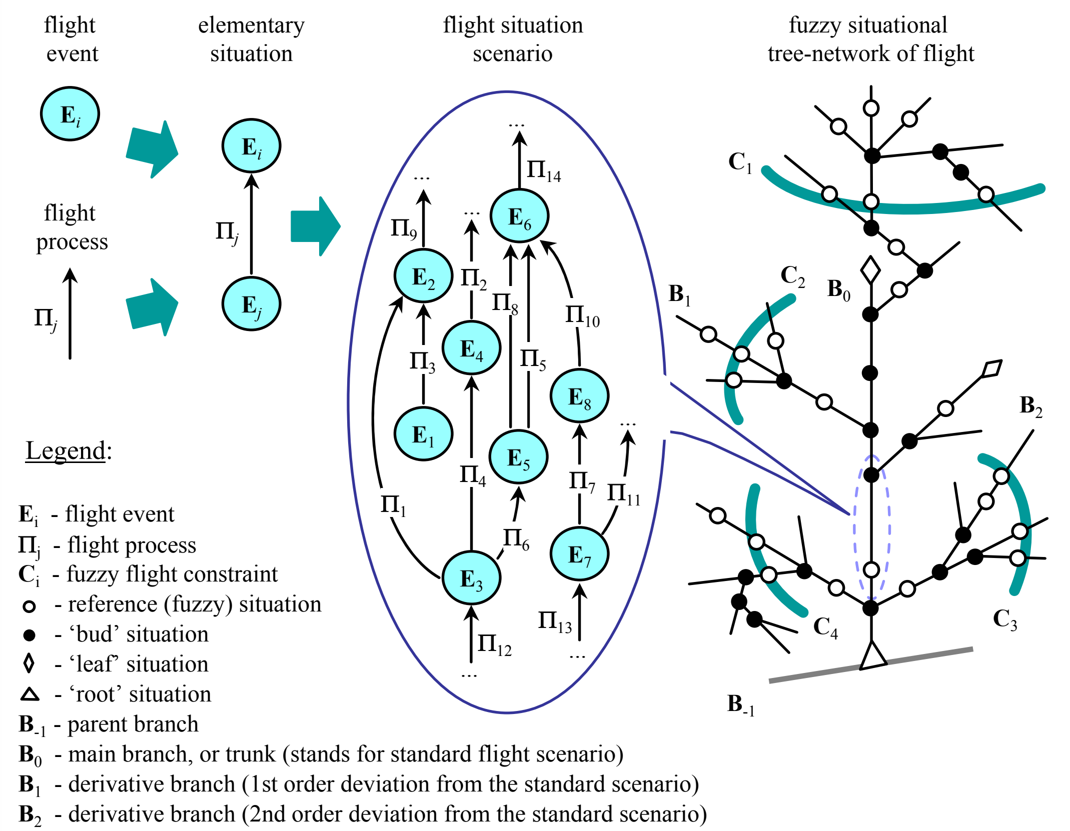
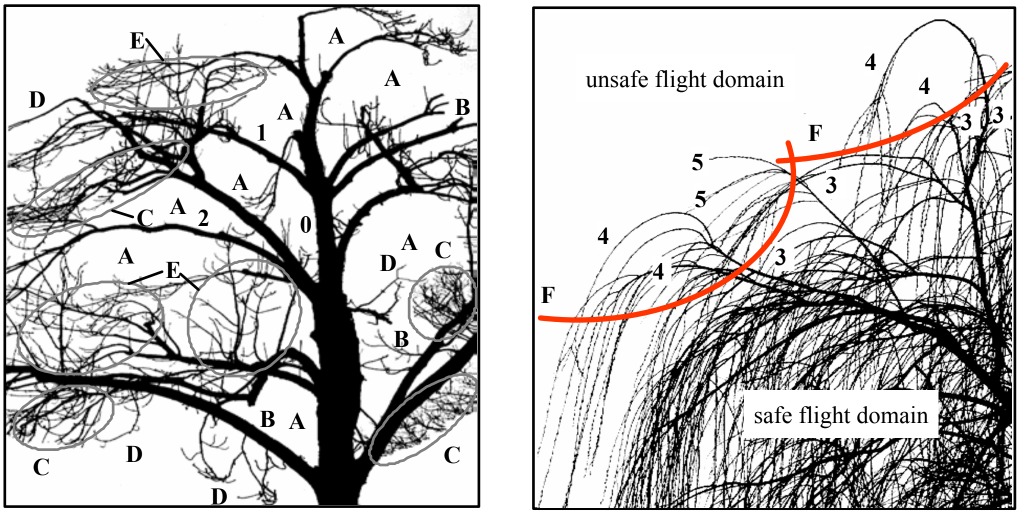


Fig. 7. Relationship between the micro- and macro-structure of flight.

(a) internal flight model of the human pilot **(b)** flight envelope protection



Legend:

0 - main branch (trunk)
1 - first-order branch
2 - second-order branch
3 - unsafe path (branch)
4 - recovery path
5 - irreversible path

A - absent knowledge (empty space)
B - decayed, shadowed or unused knowledge (dry/cut branches)
C - non-systematic knowledge (excessive/chaotic branching)
D - fragmentary knowledge (sparse branching)
E - systematic knowledge (normal branching)
F - fuzzy flight constraint

Fig. 8. Some useful patterns of natural trees.

Flight scenarios are logically connected and change in the FSTN. The FSTN is a result of autonomous flight simulation experiments with the situational model, based on scenarios. This interrelationship is schematically illustrated by Fig. 7.

The 'event-process' formalism provides a generic method to account for the various operational conditions (factors) of flight in the FSTN structure (Fig. 1). These factors are added to some reference flight scenario, either standard or already modified. As the result, the flight path deviates from its original pattern, causing the FSTN to branch. Thus, the *operational factor of flight*, Φ, is a new or modified event or process, which belongs to the set of anticipated operational conditions of flight, and which may change the original course of flight. The resulting flight path is fuzzified and added to the FSTN as a new branch. In this process, the main requirement is a comprehensive coverage of the anticipated flight domain with minimum memory resources.

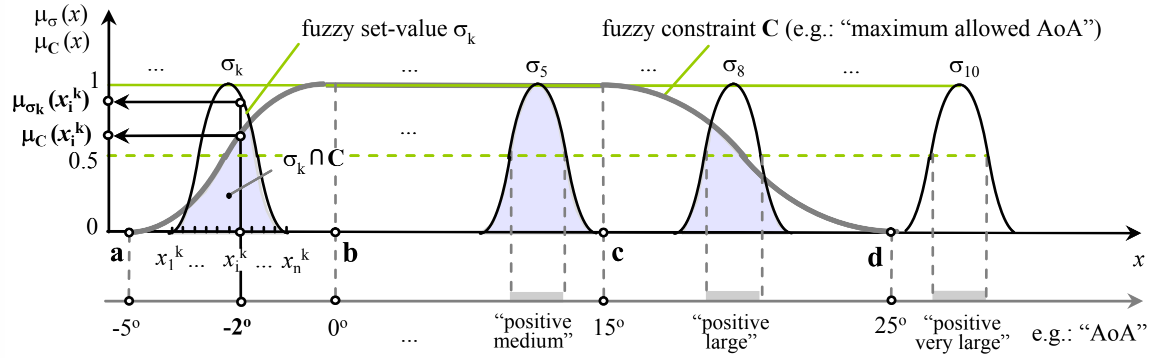
Given an emergency, the key questions for the pilot or an automatic system are to find out, which operational factors (or combinations of factors) are manageable and which are not, and under what situations. A *controllable operational factor* is an operational condition whose negative effects can be neutralized by the pilot or by an automatic control system. An *uncontrollable operational factor* is a condition whose negative effects cannot be rectified under a given situation. Examples of factors that are potentially uncontrollable include the following: engine failure, rudder hard-over, strong wind shear, heavy rain, etc.

In the FSTN, the anticipated operational factors of flight (see Fig. 1) are represented in the form of operational hypotheses. The *operational hypothesis*, **H**(Φ), is a subset of demanding operational conditions which are examined along some fuzzy branch-path. In other words, operational hypotheses are specially planned operational conditions which are used to 'implant' non-standard branches into the FSTN. A list of all the operational hypotheses for a vehicle is called the system's *operational space*. There may be more than one fuzzy branch constructed under the same hypothesis in the FSTN.

5.3. Flight situations: genetic types

The FSTN structure is comprised of the following *genetic types* of fuzzy situations (Fig. 5): root situations, leaf situations, bud situations, ordinary situations, the main branch and derivative branches.

The *root situation* (Δ) initiates a sub-domain of flight, selected for examination. It attaches its sub-tree to a 'parent branch', which represents a previous phase of flight. A *leaf situation* (◇) ends a fuzzy branch, and denotes an objective fuzzy situation of the



Degree of compatibility between fuzzy contraint **C** and fuzzy value σ_k:

$$\mu_C(\sigma_k) = \frac{\text{card}\,(\sigma_k \cap C)}{\text{card}\,(\sigma_k)}, \text{ where } \text{card}\,(\sigma_k \cap C) = \sum_{i=1}^{n} \boldsymbol{min}\,[\mu_{\sigma k}(x_i^k), \mu_C(x_i^k)], \ \text{card}\,(\sigma_k) = \sum_{i=1}^{n} \mu_{\sigma k}(x_i^k)$$

Fig. 9. Fuzzy constraints and fuzzy values of a linguistic flight variable.

flight control scenario; the latter is a subset of the flight situation scenario. The *main branch*, or trunk, is a branch constructed according to the main flight scenario. *Derivative* (secondary) *branches* of the first, second or a higher order implement modified scenarios as a result of the actions of operational factors. A branch of any order may also include an arbitrary number of ordinary and 'bud' situations. The *ordinary situation* (**o**) is used to monitor the evolution of flight situations with respect to flight constraints. In addition to this function, the *bud situation* type (●) is used for implanting new branches.

Every FSTN has its characteristic 'genetic code', which determines its structure, shape, capacity, comprehensiveness, and specialization. This property is called the FSTN genotype. The following elements constitute the *FSTN genotype*: main flight scenario, duration of a fuzzy transition (i.e., a time step for branch stratification in by ● and **o** situation types), a list of examined operational factors and their levels, and rules for combining operational factors into hypotheses, etc. The FSTN genotype is determined by the purpose of the intelligent flight support technology (control, guidance, navigation, safety, assistance, training, combat, or other).

Nature offers perfect examples of the structure of fuzzy situational knowledge trees for various practical applications. A model of a human pilot's tactical experience is depicted in Fig. 8a. This model helps explain advantages and shortcomings of the pilot's internal model of flight, and the pilot's behavior in complex situations. A weeping willow (see Fig. 8b) may be helpful to specify the structure of a fuzzy situational tree-network for flight-envelope protection and pilot assistance.

5.4. Fuzzy flight constraints

To account for the uncertainty of the knowledge of the vehicle's flight envelope, operational constraints in the FSTN are described by fuzzy sets. The *fuzzy flight constraint* **C** is a fuzzy set built over the universe of discourse of a numeric flight variable x. It is defined by four reference points (**a**, **b**, **c**, **d**) of its numeric carrier (Fig. 9). The *degree of compatibility of a fuzzy state and fuzzy constraint*, $\mu_C(\sigma_k)$, is measured using the operation of intersection for fuzzy sets. This measure can be used to assess the degree of danger of alternative flight paths (see Fig. 9). Note that within the FSTN structure, the fuzzy flight constraint looks like an external object, or fuzzy strip, attached to one or several branches (Fig. 5). The nomenclature and positions of fuzzy flight constraints in the FSTN are revealed after the completion of its construction process.

5.5. Flight situation safety status

Fuzzy situations, which are located at some constraint (from its safe and unsafe sides), can be categorized according to their safety status. Each such boundary fuzzy situation can be assigned a characteristic *safety status* (Burdun, 1998). A list of characteristic safety statuses is as follows: the border of the operator's 'comfort zone', **OK**; the beginning of constraint monitoring, **M**; the warnings—first (!), second (!!), and last (!!!); a constraint-infringement situation, *; the beginning of automatic recovery, ⇑; an irreversible situation, ⇓; a catastrophic situation, ⊗; a safe return (to the flight envelope) situation, ^{R}. The meanings of these situations are clear from their names and graphical symbols. The recognition criteria for these safety statuses are discussed in (Burdun, 1996).

A time history of a flight variable can be colored using four *safety colors* (Burdun, 1998): *green*, ξ_G, if the current value of a corresponding numeric variable is within acceptable limits; *amber*, ξ_A, if the variable enters the uncertainty interval [**a**; **b**] or [**c**; **d**] of the fuzzy constraint; *red*, ξ_R, if the variable violates its constraint beyond **a** or **d**, and *black*, ξ_B, if flight cannot be continued due to airframe disintegration, or other fatal cause. The concepts of situation safety status and situation safety color can be used to partition the situational flight domain into characteristic *safety zones*, namely: the *green zone* (the situations located between the **OK** and **M** surfaces), the *amber zone* (between **M** and !!), the *red zone* (between !! and $\Downarrow$), and the *black zone* (between $\Downarrow$ and $\otimes$). In dynamic analyses of flight, this partition can be used to visualize the knowledge stored in the FSTN.

5.6. FSTN construction principles

The construction and analysis of the FSTN for realistic applications is a computationally demanding task because of the extremely large volume and complex structure of non-standard flight domains. A possible solution is to emulate a growth mechanism of trees and other natural plants (MacDonald, 1983). Theory of fractals may be useful as well (Mandelbrot, 1983). However, a pre-requisite is the availability of a comprehensive mathematical model of the vehicle dynamics and control. In particular, in safety applications such a model should be capable of describing the system behavior at the operational constraints, and under multiple operational conditions.

The FSTN is constructed for a specific phase of flight, lasting between 10–20 and 90–120 s. The duration depends on the vehicle type and flight mission. An autonomous flight situation model and FSTN genotype are used for this purpose. The main branch, or trunk, of the FSTN is formed according to the main scenario as a result of numeric integration of differential equations of the vehicle motion. The internal structure of the trunk may be unfolded as an ordered cause-and-effect chain of flight events and flight processes, lined up in the upward direction (Burdun, 1996). Ordinary (**o**) and bud (•) situation types are defined along a branch according to the FSTN genotype. A derivative branch can be implanted into any bud situation according to a new scenario. Rules for introducing these changes are also defined in the FSTN genotype. Derivative branches are planted in a similar way to the main branch.

An example of FSTN construction and FSTN-based optimization and modeling of hypersonic maneuvers of a transatmospheric vehicle under complex operational conditions is described in (Burdun and Parfentyev, 1998).

5.7. FSTN design process

The *FSTN design process* includes the following main phases or algorithms: specification of main fuzzy metrics in situational flight space (fuzzy measurement scales), development of the standard flight situation scenario, specification of the FSTN genotype, FSTN branching, FSTN growth monitoring, safe flight-path optimization, analysis and verification of the FSTN content, and the representation and generalization of knowledge stored in the FSTN. These phases are implemented in special algorithms.

FSTN branching is a central component of the design process. It includes the following steps: (1) growth of the FSTN crown towards operational constraints, (2) infringement of the constraints by fuzzy flight-path-branches under key operational hypotheses factors, and (3) reverse branching of the FSTN from unsafe situations towards the safe flight envelope.

The FSTN crown is specially shaped to thread the situational domain of interest from some reference (base) situation towards the operational constraints. Such a domain may include, for example, a flight accident and its 'neighborhood' (Burdun, 1998). Another example is a domain of takeoff situations under anticipated conditions described in a pilot's manual. The primary goal of FSTN branching is to examine zones of safe and unsafe flight modes around a reference situation under various operational hypotheses. Another goal is to 'hit' as many constraints as possible, and penetrate them from both sides. As the result, the cause-and-effect structure of a complex flight domain can be revealed under multiple conditions and at the constraints, where the chances of 'chain reaction' are high.

5.8. Safety characteristics of FSTN components

When the FSTN branching process has been accomplished, *flight safety characteristics* can be measured for each fuzzy situation. This list includes: safety status if applicable, safety color, distance to the nearest flight constraint (in time, altitude, speed or other units), distances to the situations of $\Uparrow$, $\Downarrow$, $\otimes$, or $^{\text{R}}$ type, degree of danger (safety), uncontrollable factors, recovery inputs, and others. The *degree of danger* of a fuzzy situation is the share of dangerous fuzzy situations that belong to a sub-tree emerging from this situation. The safety characteristics can be used in designing the logic of intelligent flight support technologies. For example, the distance to the nearest flight constraint can be used for FSTN-based near-term flight monitoring and prediction. The position of initially assigned

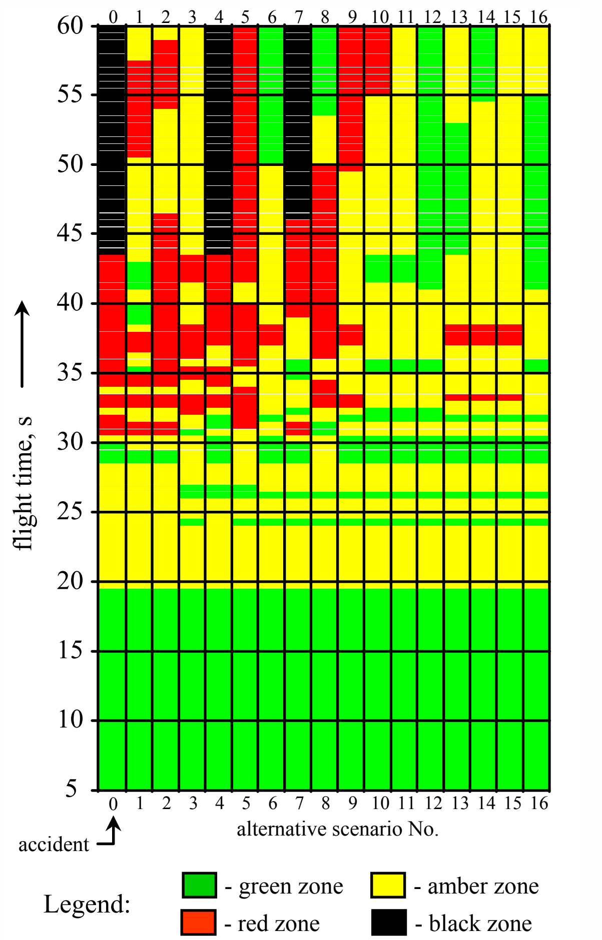


Fig. 10. Flight safety spectra of the flight accident and its 'neighborhood'.

flight constraints in the FSTN may be reviewed, based on the actual proportion of irreversible and catastrophic situations (⇓ and ⊗) behind this constraint, recorded in the FSTN.

Safety characteristics can also be assigned to fuzzy transitions and fuzzy branches, and the flight safety spectrum is one of them. This *flight safety spectrum* Σ, is basically a colored strip, which graphically indicates changes of the 'hottest', among a monitored subset of flight variables, safety color along some flight path. The flight safety spectrum can be calculated using a formal relationship introduced in (Burdun, 1998). Safety spectra for a flight accident and its 'neighborhood' of the situational tree depicted in Fig. 6 are shown in Fig. 10. It follows from the diagram that even a small subset of alternative flight scenarios helps reveal in advance possible safe and unsafe flight paths under key operational hypotheses. Note that safe flight alternatives are colored in green or amber in their final segments; ref. (Burdun, 1998) for more detail.

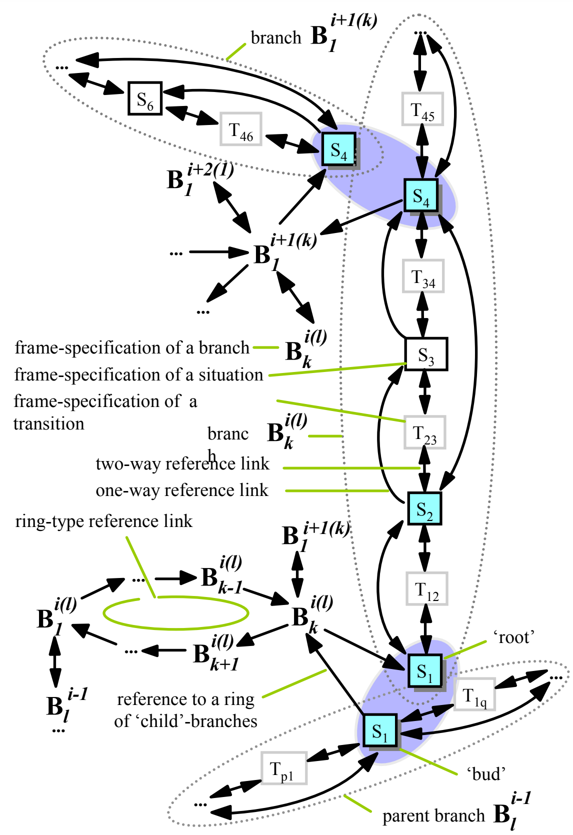


Fig. 11. FSTN representation by B-trees, frames and linked lists.

5.9. FSTN characteristics

The following *characteristics of the FSTN* or its sub-tree may be defined: main flight situation scenario, power (by situations, transitions, or branches), examined operational hypotheses, explored/protected flight constraints, and total flight time (the length of all its branches in time units). Other important characteristics include: the percentage of '*green*', '*amber*', '*red*', and '*black*' fuzzy situations, chances of safe recovery under specified hypotheses, and lists of controllable and uncontrollable factors. These characteristics may be used, for example, to compare the tactical experience of a hybrid intelligent pilot model, the pilot and an automatic system. Results of such a comparison, i.e., the level of knowledge for these agents in a particular sub-domain of flight, may serve as a criterion for assigning the authority of recovery flight control in an emergency. In particular, a list of examined (experienced) operational hypotheses and the total flight time under given conditions or at a given constraint may be useful for this purpose.

5.10. Intelligent flight envelope

The FSTN concept can be used to define the notion of an intelligent flight envelope. The *intelligent flight envelope* is basically a shell-type subset of the FSTN crown, which threads the vehicle's flight constraints in both directions. It may be called 'intelligent' because it explicitly incorporates knowledge of the operational hypotheses along the paths that cause constraint infringement (*critical operational factors*), together with the *recovery control tactics*. These fuzzy paths cross the edge of the flight envelope from safe situations (**M**) to unsafe situations ($\Downarrow$ or $\otimes$) and back (®). The positions of automatic recovery situations ($\Uparrow$) in the FSTN can be determined dynamically, during flight. They are calculated based on the results of near-term predictions of possible flight paths, which may emerge from a current fuzzy situation under key operational hypotheses. One of the criteria could be not to exceed some critical proportion of unsafe situations (which have status $\Downarrow$ or $\otimes$) in the total number of situations emerging from the current situation.

5.11. Implementation issues

Dynamic data structures can be used for implementing the FSTN concept on a computer. These include frames, linked lists, general *M*-way balanced trees, and some others. An illustration of a sub-tree from the FSTN represented by dynamic data structures is demonstrated in Fig. 11.

6. Intelligent flight technologies

An FSTN-based hybrid intelligent pilot model and its knowledge base, FSTN, are suggested as a formal basis of advanced technologies for flight safety enhancement. A brief overview of these systems follows.

6.1. Potential applications

There are several possible avenues for implementing the FSTN concept onboard. These include, but are not limited, to the following:

- intelligent pilot-vehicle interface
- automatic flight-envelope protection
- automatic prevention/resolution of conflicts in close free-flight air space
- autonomous (robotic) flight, including multiple intelligent vehicles
- knowledge-centered pilot training and pilot assistance, and
- virtual testing and certification of the vehicle's flight envelope in design.

The first three technologies from this list are introduced below.

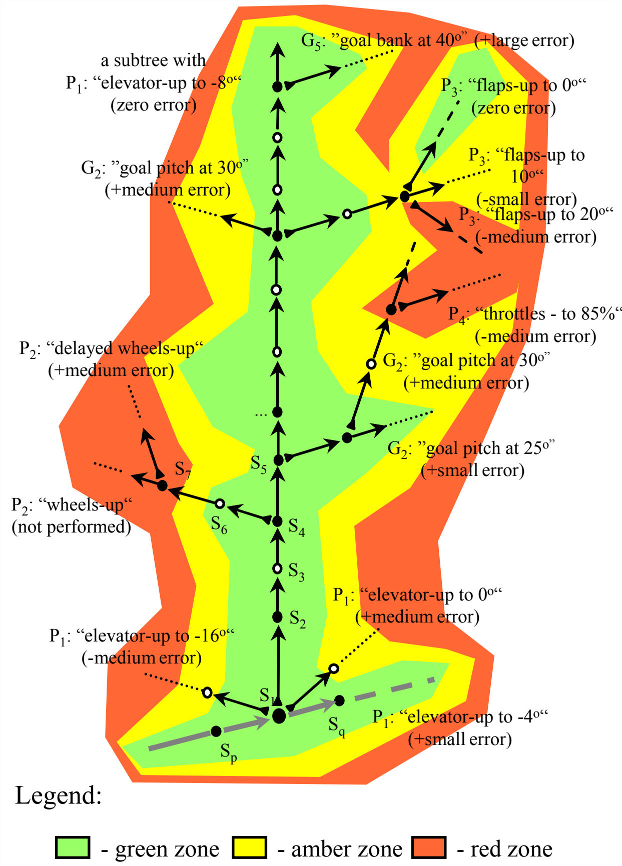


Fig. 12. Notional layout of the Situational Forecast Display (SFD).

6.2. Intelligent pilot-vehicle interface

The *intelligent pilot-vehicle interface* may be defined as a real-time process of exchanging knowledge between the hybrid model and a human pilot in coherent, knowledge mapping formats. This task can be accomplished through a notional system called the *Situational Forecast Display* (SFD). The SFD is a two- or three-dimensional graphic color mapping of a subset of knowledge from the FSTN, relevant to some reference situation (Fig. 12). It represents a sub-tree of interrelated fuzzy flight paths, which may originate from this situation *if* certain operational hypotheses step into action. This is why the SFD may be called a 'what-if' flight analysis tool. The operational hypotheses for examination can be specified and modified by the pilot to backup his (her) internal model of a complex flight situation domain.

Unlike an ordinary instrument, which measures current flight states, the SFD provides the pilot with knowledge of a flight situation domain anticipated in the near future (in 5–25 s). For this purpose, a subtree of information relevant to the reference (current) situation, normally located in the bottom of the dis-

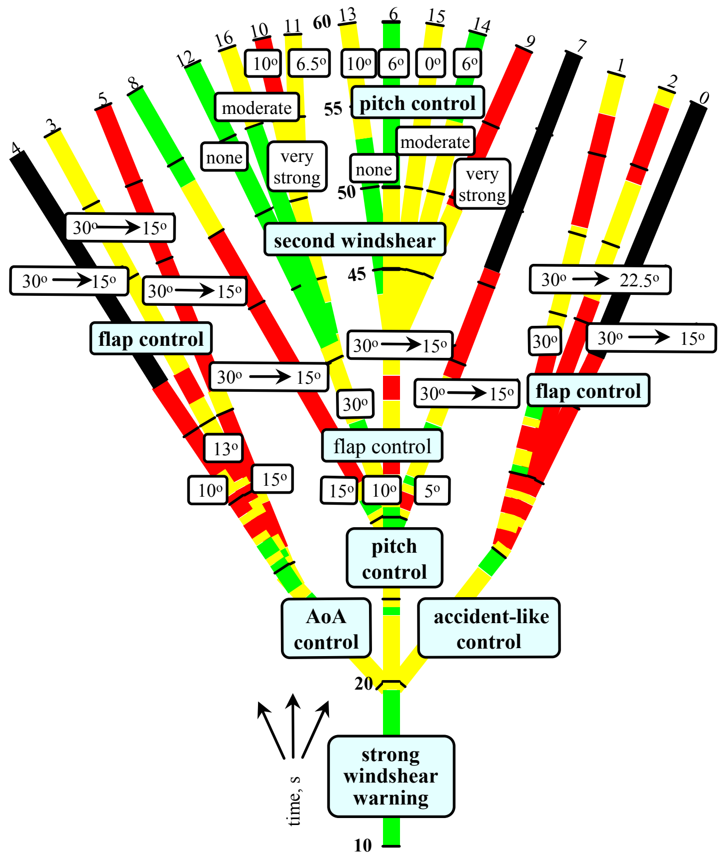


Fig. 13. Basic situational forecast display 'Takeoff under microburst conditions'.

play, is loaded from the FSTN and projected on a screen to depict short-term flight paths several seconds ahead. Its branches stand for key operational factors of flight (hypotheses). This picture is updated with a frequency as low as 0.5–2 Hz, depending on the vehicle dynamics, flight mission, pilot's characteristics, and the level of danger of the current situation and its developments.

The resulting image may be considered as a virtual 'safety valley' (see Fig. 12). Red and black 'hills' in this valley indicate critical flight modes to avoid (i.e., no collision is allowed with the 'hills'). The pilot can examine its topology and select a safe flight path-branch (scenario). This process can be implemented through a tactile display by applying a finger touch control to the desired tree's segment. Alternatively, a laser scanning could be used to locate the pilot's eye focus point within the tree. After confirmation of the choice by some distinct command, the selected path is taken for realization. The associated control tactics may be engaged automatically or manually.

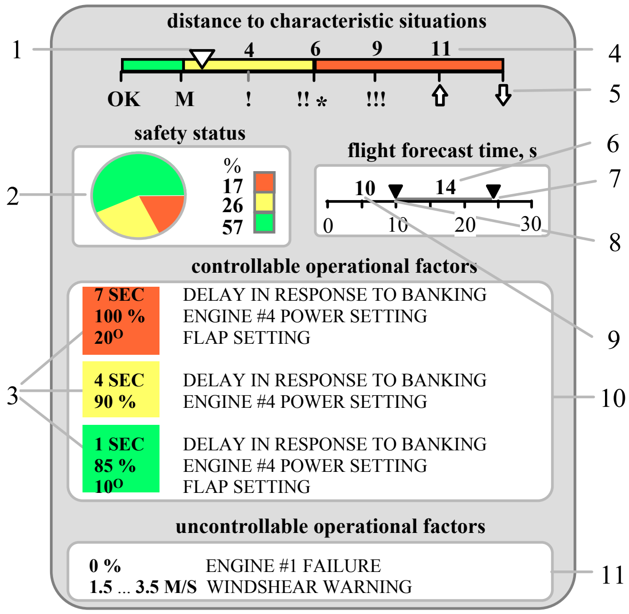
Thus, the SFD function is in coherence with the principles of pilot decision-making, and with the organization of a human pilot's tactical experience in long-term memory. This allows the pilot-vehicle interface to be implemented on the level of knowledge, not data. Also, the pilot's decisions are situation-based. As the result, it is expected that a more thorough dynamic planning of flight can be achieved under complex (multi-factor) situations.

An example of a basic situational forecast display for microburst conditions is shown in Fig. 13. It maps a situational flight domain around the flight accident represented in Figs. 3, 6, and 10—see Burdun (1998) for further details.

6.3. Automatic flight-envelope protection

The *automatic flight envelope protection* task includes the following functions:

- monitoring of the current distance to the nearest operational constraints
- calculation of the chances of safe recovery from the situations located at and beyond the edge of the envelope
- identification of the critical zone [⇓; ⊗] at the nearest constraint



Legend:

1 - marker of the vehicle current position with respect to a critical constraint
2 - current chances of 'red', 'amber' and 'green' outcomes of flight
3 - processes leading to the 'red', 'amber' and 'green' zone, respectively
4 - time (in seconds) to characteristic situations
5 - characteristic safety types of flight situation
6 - depth of future flightpaths analysis
7 - forecast end time marker (with respect to the reference/current situation)
8 - forecast start time marker (with respect to the reference/current situation)
9 - relative time when forecasts start
10 - aiding messages (controllable operational factors) also produced by audio means
11 - aiding messages (uncontrollable factors) also produced by audio means

Fig. 14. Notional layout of the Flight Safety Indicator (FSI).

- advising the pilot of the uncontrollable factors that are likely to bring the vehicle to this zone
- search for the recovery control tactics and fuzzy flight path(s) to bring the vehicle back into the safe envelope
- suggestion or execution of the recovery tactics and monitoring the return flight path.

The goal of this process is to prevent the vehicle from entering a zone of irreversible flight paths under multi-factor situations.This task can be realized by means of a *Flight Safety Indicator*, or FSI (Burdun, 1998). A notional layout of the FSI is depicted in Fig. 14. The instrument's input includes key operational hypotheses and flight variables which the pilot wants to monitor (not shown), and other parameters (shown in Fig. 14). Based on this information, a sub-tree is loaded from the FSTN for processing. Given the key hypotheses and the desired forecast time span (**6**), the overall chances of safe, marginal, dangerous, and fatal outcomes of the current situation are calculated and displayed on the sector diagram (**2**). The indicator also depicts a current position (**1**) of the vehicle with respect to the nearest constraint, and the distances (**4**) to the characteristic flight safety situations (**5**) that are located at this constraint. Also displayed are the events and processes of those unsafe scenarios that are likely to bring the vehicle to the edge of the flight envelope, i.e., to the red zone [!!; ⇓]. Alternatively, an automatic speech synthesizer may be used to convey these messages to the pilot. The instructions which the pilot should follow to recover from a critical situation are available as well. The recovery path can be derived from the FSTN using the technique described in (Bellman and Zadeh, 1970). The flight envelope protection function may also be executed automatically (Burdun, 1998).

6.4. Automatic resolution of conflicts in close free-flight air space

Let a system of several heterogeneous vehicles merge arbitrarily in close free-flight air space. Also, the vehicles' flight paths may be affected at any time by various demanding conditions (see Fig. 1). The problem is how to organize, without external supervision, the system's collective behavior in order to avoid impending collisions and near-miss cases under complex (multi-factor) conditions (Burdun and Parfentyev, 1999). The overall objective is to foresee in advance possible conflicts in close air space.

In a system of two vehicles, **A** and **B**, the conflict management process can be arranged as follows (Fig. 15). Each vehicle scans a situational sub-domain ahead of it with the objective of identifying impending conflicts with the other vehicle. This domain represents a 'what-if' neighborhood of the intended flight path for the vehicle. The operational hypotheses selected for monitoring by the system normally account for actually present and anticipated conditions. They may also reflect the pilot's desire to back up his (her) knowledge of some critical flight domain. For each vehicle a sub-tree from its FSTN is projected into close air space, forming a cone of possible fuzzy paths (see Fig. 15). This cone is translated along the vehicle's intended flight path as the vehicle moves forward. The objectives of this process are to (1) detect zones in close air space, where fuzzy flight paths of the two vehicles intersect under one or several key operational hypotheses, (2) analyze these zones, and (3) find fuzzy paths and recovery tactics to resolve the conflict dynamically.

In the hypothetical situation depicted in Fig. 15, the vehicles are facing five impending conflicts. Once identified, these conflicts are sorted by the expected occurrence times. Zones of these conflicts in the protected air space are declared as prohibited. Then, a subset of interrelated pairs of the operational hypotheses, under

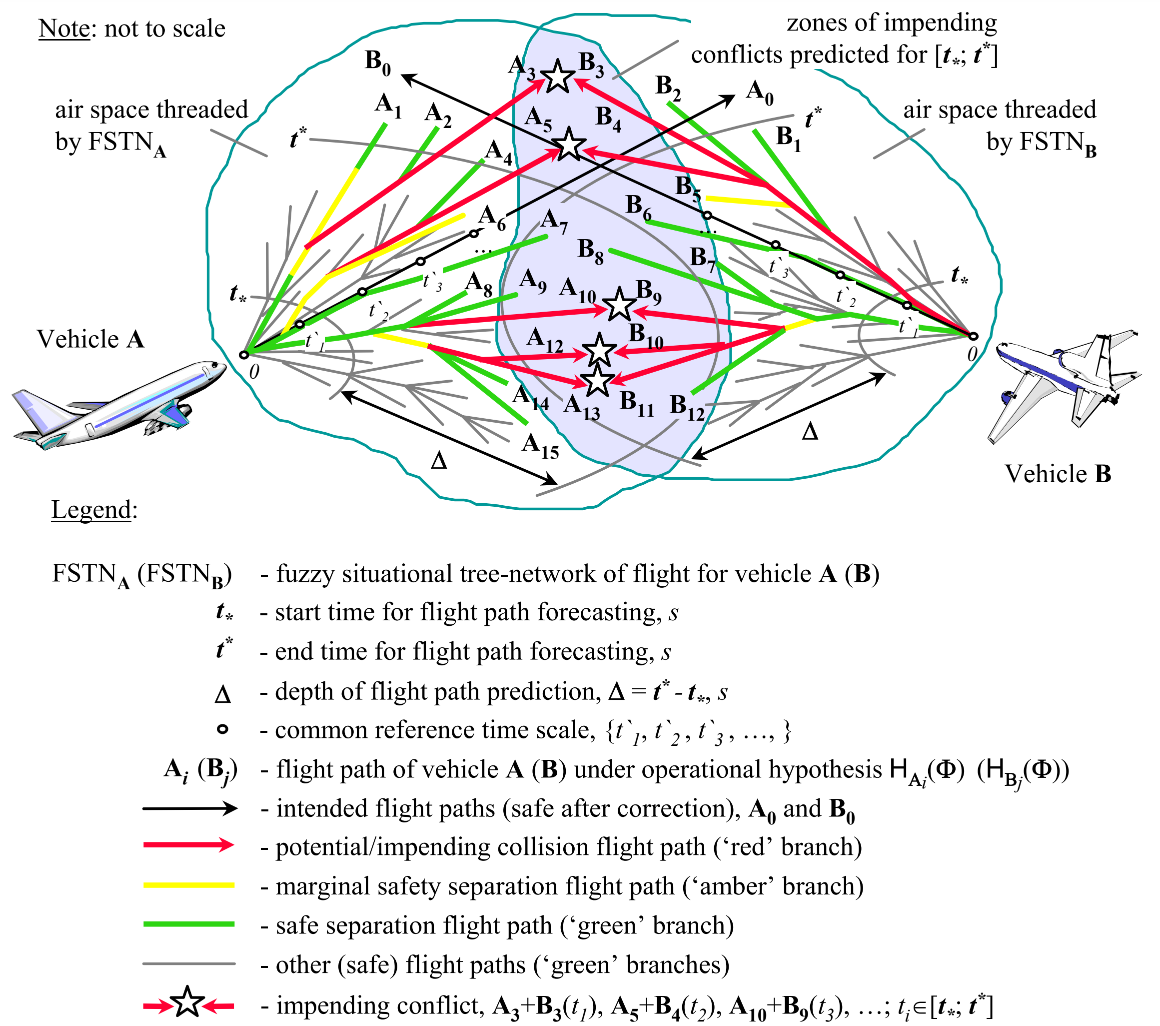


Fig. 15. FSTN-based flight-path prediction for collision prevention/resolution in close air space.

which the vehicles can be brought into these zones, is formed. These pairs are placed on the top of the checklist of the health and weather monitoring systems for both vehicles. Further, a joint recovery tactic is sought in $FSTN_A$ and $FSTN_B$ if: (1) some pair of operational hypotheses becomes actual, and (2) both vehicles are still on to the conflicting fuzzy branches, and (3) chances of recovery become lower than some safety margin. If a conflict threat persists and a decision is made to recover, either by the pilot or automatically, these tactics are applied to **A** and **B** according to the flight control scenarios of the recovery branches stored in the $FSTN_A$ and $FSTN_B$. Obviously, the most critical operational hypotheses, which include uncontrollable and other strong factors, must be accounted for first in recovery tactics. Knowledge of impending conflicts can be conveyed to the pilot, for example, in the form of a modified Situational Forecast Display. This display format can be adapted to account for multiple-vehicle system.

7. Conclusion

Given a complex flight situation, uncontrollable cause-and-effect links (a 'chain reaction') may be spontaneously triggered in the 'pilot-vehicle-operational environment' system. This may compromise flight safety. The system behavior in emergencies is a dynamic superposition of the laws of aerodynamics, flight mechanics, and propulsion. The outcome of these complex relationships has a branching structure, which is very sensitive to the contributory operational factors. Flight incidents of a 'chain reaction' type may be pre-programmed in the system logic if this important branching property of the system behavior is ignored in flight safety design.

More physics-based knowledge of multi-factor operational domains of flight is required onboard. The purpose of this information is to help the pilot predict the system dynamics, at the edge of the flight envelope and under multiple conditions. The autonomous flight modeling and artificial intelligence techniques offer a feasible solution to this problem. By means of a fuzzy situational tree-network of flight (FSTN) it is possible to predict near-term fuzzy flight paths, both safe and unsafe, which may originate from a current situation under the effect of several key operational factors. The FSTN may be used as a generic knowledge basis of new intelligent technologies for implementing flight safety as an inherent property of flight vehicles. The purpose is to identify and avoid the propagation of a 'chain reaction' type flight accident under multiple operational conditions. These intelligent technologies are suggested as an affordable solution to the emerging flight-safety problem in advanced vehicles.

Potential applications include: intelligent pilot-vehicle interfaces, automatic flight envelope protection, autonomous (robotic) flight including multiple intelligent vehicle systems, automatic resolution of conflicts in a close free-flight navigation space, knowledge-centered pilot assistance and pilot training, and virtual testing and evaluation of aircraft flight envelopes in design. In general, the role of intelligent flight technologies can be thought of as a kind of 'future-looking flight situation radar' on board the vehicle.

Acknowledgements

The authors wish to thank Dr Daniel DeLaurentis (Georgia Institute of Technology, USA) for useful discussions and help. Special thanks are extended to Mr Lionel Guibellini and Mr Philippe Hemeury (Aerospatiale) and to Mr Jean-Pierre Cachelet (Airbus) for their multi-aspect help and discussions of these ideas at Cranfield University, UK.

References

Bellman, R.E., Zadeh, L.A., 1970. Decision-making in a fuzzy environment. NASA Contractor Report, NASA CR-1594.

Burdun, I.Y., 1996. An AI situational pilot model for real-time applications. In: Proceedings of the 20th Congress of the International Council of the Aeronautical Sciences, Sorrento, Napoli, Italy, 8–13 September 1996 (ICAS '96), vol. 1. AIAA, pp. 210–237.

Burdun, I.Y., 1998. The intelligent situational awareness and forecasting environment (the S.A.F.E. concept): a case study (Paper No. 981223). In: Proceedings of the SAE Advances in Flight Safety Conference and Exhibition, 6–8 April 1998, Daytona Beach, FL, USA (P-321). AIAA-SAE Aerospace, pp. 131–144.

Burdun, I.Y., Mavris, D.N., 1997. A technique for testing and evaluation of aircraft flight performance in early design phases (Paper No. 975541). In: Proceedings of the World Aviation Congress (WAC '97), Anaheim, October 1997. AIAA.

Burdun, I.Y., Parfentyev, O.M., 1998. Analysis and optimization of hypersonic maneuvering of a transatmospheric vehicle under uncertainty using fuzzy trees (Paper No. AIAA-98-4976). In: Proceedings of Seventh AIAA/USAF/NASA/ISSMO Symposium on Multidisciplinary Analysis and Optimization, 2–4 September 1998, St Louis.

Burdun, I.Y., Parfentyev, O.M., 1999. An AI knowledge model for self-organizing conflict prevention/resolution in close free-flight air space. In: Proceedings of 1999 IEEE Aerospace Conference, Snowmass, Colorado, March 6–13, 1999 (to be published).

Chatrenet, D., 1996. Flight safety aspects with modern flight control systems. In: Proceedings of the 20th Congress of the International Council of the Aeronautical Sciences, Sorrento, Napoli, Italy, 8–13 September 1996 (ICAS '96), vol. 1. AIAA, pp. 336–340.

Goldin, D.S., 1997. The three pillars of success for aviation and space transportation in the 21st century, A speech given before the Aero Club, AIAA, and NAC, Thursday, 20 March, 1997.

Graeber, C., Billings, C.E., 1989. Human-centred automation: development of a philosophy. In: Proceedings of the Aviation Safety/Automation Conference (NASA CP-3090), 11–12 October 1997, pp. 91–99.

MacDonald, N., 1983. Trees and Networks in Biological Models. John Wiley and Sons.

Mandelbrot, B.B., 1983. The Fractal Geometry of Nature. WH Freeman & Company, NY.

Wirth, N., 1988. Programming in Modula-2. Springer-Verlag p. 87.

Zadeh, L.A., 1976. A fuzzy-algorithmic approach to the definition of complex and imprecise concepts. Int. J. Man-Mach. Studies 8 (3), 249–291.

Ivan Y. Burdun. Ivan graduated as Aeronautical Mechanical Engineer from the Riga Civil Aviation Engineers Institute (RCAEI), ex-USSR. His PhD thesis (1982, RCAEI) was with fuzzy sets based computer simulation of aircraft flight dynamics and human piloting under complex conditions. In 1983–1992 Dr Burdun worked as Senior Researcher at Flight Modeling Department of the Riga Experimental Center for Aeronautical Research of the USSR State Research Institute of Civil Aviation (GosNII GA). He had carried out over 20 research contracts for several aerospace customers as Principal Investigator and Co-Investigator. In 1993–1996 he received a second PhD training in Avionics and AI under an ORS Award at Cranfield University, UK (the thesis writing up is not finished). He has implemented autonomous situational models of flight for 19 aircraft types. Using these models, over 30 practical problems were studied in the sectors of aircraft practical aerodynamics, flight control, and flight safety. He has authorized over 85 technical reports and other publications in Russian and English, three applied techniques, one invention, and many Russian–English and English–Russian aviation translations. His research interests include: hybrid intelligence pilot models, fuzzy situational decision trees, computer simulation of complex dynamics of the 'pilot–vehicle–operational environment' system, flight accident reconstruction and neighborhood analysis, aircraft virtual testing under multiple conditions, and onboard AI technologies for flight safety. At present, Dr Burdun works in the Aerospace Systems Design Laboratory, School of Aerospace Engineering, Georgia Institute of Technology. His responsibilities at Georgia Tech include research and teaching in the sectors of mathematical modeling, computer simulations and artificial intelligence for flight safety.

Oleg M. Parfentyev. Oleg graduated as Avionics Engineer from the Riga Civil Aviation Engineers Institute (RCAEI), ex-USSR. In 1993 he received a PhD degree in Flight Control and Cybernetics from

the Department of Aircraft Automation of RCAEI. He worked as a Research Assistant and Research Engineer with Departments of Applied Mathematics and Aerodynamics, RCAEI, and Department of Avionics, the Riga Air Force Engineering College (1984–1992). Dr Parfentyev participated in research and development projects for several major aerospace customers in the ex-USSR, including the State Research Institute of Civil Aviation, Molniya Scientific-Production Consortium, Center for Cosmonaut Training, Scientific-Research Institute of Space Medicine, and Air Force Engineering Academy, at the level of Co-Investigator and Principal Investigator. He has authorized over 30 technical reports, papers and conference presentations. His current research interests include AI flight control, pilot-vehicle anthropomorphic interface, fuzzy situational decision trees, and advanced pilot training. He has piloting experience with several Russian and Western aircraft types (over 1700 flight hours, 12 airplanes, a helicopter, and 8 gliders). He also gained flight test experience with several home-built airplanes. At present, he is a flying instructor in sport aerobatics and soaring. He won several first and second prizes in team competitions in soaring. Dr Parfentyev is affiliated with the Siberian Aeronautical Research Institute (SibNIA, Russia) as Scientific Advisor to Chairman.