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Implementation of a flight operations risk assessment system and identification of critical risk factors

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Approximate reasoning.

Abstract. This study presents the implementation of a Flight Operations Risk Assessment System (FORAS) for an airline company, as well as a decision support tool for identifying factors that critically determine the risk of a flight. The FORAS risk model is a hierarchical tree structure that breaks down the concerned operation risk to subcomponents and risk factors. The relation between a risk and its subcomponents is described by a fuzzy inference system. The use of fuzzy inference systems enables quantification of qualitative risk assessments by domain experts. The inference of the operation risk is obtained through approximate reasoning. Algorithms are developed to identify critical risk factors based on the concept of the sensitivity of a risk factor and a heuristic search. Experiments based on practical data are conducted to evaluate the validation and performance of the FORAS model.

1. Introduction

The primary risks of the aviation industry fall into four categories [1]: hazard, strategic, financial, and operational. Operational risks refer to those risks associated with maintenance, reliability, scheduling, etc. The above-mentioned operations directly link to flight safety and its failure is extremely severe. The present study, thus, focuses on the management of flight operations risk and the support of dispatch decisions.

The International Air Transportation Association (IATA) classifies the causes of flight risk into five categories, namely, human, technical, environmental, organizational, and unknown. According to an investigation of commercial jet airplane accidents between 1996 and 2005, 55% were related to flight crews, 17% to aircrafts, and 13% were weather relevant [2]. According to IATA classification, the flight crew belongs to the category of human, the aircraft is a technical problem, and weather is in the category of the environment. These three categories account for 85% of causes, among which, human related factors are particularly critical.

Accidents of Controlled Flights Into Terrain (CFIT) was the most frequent accident category between 1987 and 2005 [2], and was the second most frequent between 2001 and 2010 [3]. CFIT refers to accidents in which an airworthy aircraft, under pilot control, is unintentionally flown into the ground, a mountain, water, or an obstacle [3]. In addition to environmental factors, the main cause of CFIT is an incorrect approach to the airport. Approach and landing (ALR) are the phases of a flight during which fatal accidents occur most often, accounting for 36% of accidents, while the phase of take-off and initial climb accounted for 17%, being the second most frequent [3].

From the above discussion, it is noted that

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approach-and-landing and take-off-and-initial-climb are the two phases during which accidents occur most frequently, and humans were often the major factor causing the accident. Thus, current aviation safety risk assessment systems generally focus on the approach and landing phase and human-related risk factors, e.g. Flight Operation Quality Assurance (FOQA), the Aircraft Performance Risk Assessment Model (APRAM), the Aviation System Risk Model (ASRM), the Flight Operations Risk Assessment System (FORAS), etc. The aims of these systems are to identify risk factors that potentially lead to the occurrence of accidents, and to adopt preventive actions to eliminate such risks.

FOQA is the process of collecting and analyzing data from flights to improve the safety and efficiency of flight operations. It basically involves collecting flight data, analyzing it, reporting any unsafe occurrences using flight data and flight trends, putting corrective actions into place to reduce or remove unsafe trends, and monitoring flight data to ensure unsafe flight trends are not occurring [4]. The concept of APRAM is similar to FOQA, but it emphasizes the use of computer models to automate the analysis process and incorporates expert opinion. It uses both empirical data and knowledge-based rules to quantify the risk of an incident/accident. APRAM processes aircraft data available from Digital Flight Data Recorders (DFDRs) and Quick Access Recorders (QARs). The model uses flight data to identify non-normal flight performances, called exceedance, which defines an occasion when the aircraft exceeds its normal operating limits. The exceedance data is combined with contextual factors falling into several categories. These include environment, process/procedure, system, and human.

ASRM aggregates ideas and concepts concerning aircraft accident causal modeling into a Bayesian Belief Network (BBN) to compute a relative safety risk metric [5]. A BBN is a modeling method in the area of decision making under uncertainty [6]. The BBN modeling approach explores the probabilistic interdependencies among individual, task/environmental and organizational factors that lead to accidents. The intent of the model is to provide a systematic, structured approach to understanding aircraft accident causality and to provide a means for performing risk assessments of new aviation safety products.

Quantitative assessment of aviation risk is particularly challenging because undesired events are extremely rare; causal factors are difficult to quantify and are nonlinearly related [7]. On the other hand, abundant safety experience and knowledge are embodied in the personnel of an aviation organization [7]. If such experience and knowledge can be elicited and encapsulated in a computer model, the difficulty of aviation risk quantification may be alleviated. Based on the concept of encapsulating human expertise in the risk model, FORAS [7-10] incorporates fuzzy inference systems in its structure to represent human experience and knowledge, regarding aviation risk assessment, to produce a quantitative index for proactively assessing aviation risk.

This study presents the implementation of an approach and landing risk model by FORAS for an airline company. The implementation issues include system architecture, modeling techniques, system operations, and critical risk factor identification. The focus of FORAS is prevention, and to take a proactive approach to identify mishap precursors [7]. This study also develops algorithms to identify the critical risk factors that potentially lead to a mishap. When the risk assessment by the proposed system indicates a potential flight risk, the dispatcher can alter the operations of the flight, based on these suggested critical factors, to reduce the potential risks of the flight. The rest of this paper is organized as follows. Section 2 presents the concept, structure, and methodology of FORAS. The third section discusses the system implementation of FORAS and its operations. Section 4 presents the algorithms for identifying the critical risk factors of a flight. Computational experiments are carried out in Section 5, and finally, conclusions are given in Section 6.

2. FORAS

The FORAS project, started in 1997, is the fulfillment of an initiative by the Icarus Committee, which is affiliated with the Flight Safety Foundation (FSF), USA. The goal of FORAS is to develop a quantitative index for proactively assessing aviation risk, focusing on the recognition of risk factors involved in aviation safety instead of the emphasis on accident rate measurements [7].

The emphasis of FORAS is to represent the risk of a flight as a chain of flight operations in terms of risk factors. The risk model is represented as a hierarchical structure, which breaks down the concerned operation risk of the flight, e.g. Approach and Landing Risk Value (ALRV), to its causal operation risks, as demonstrated in the example in Figure 1. This example illustrates that the approach and landing risk is a consequence of three causal risks, namely, crew functionality risk, aircraft functionality risk, and sector threat risk. Crew risk is further decomposed into inter-crew communication risk, experience risk, and stress risk. Such decomposition continues until input data can be directly obtained from actual operations; e.g. experience pairing and English proficiency in the example.

The risk model of FORAS is an organized set of causal factors, where a causal relation exists in each subset of a risk and its causal risks. For the

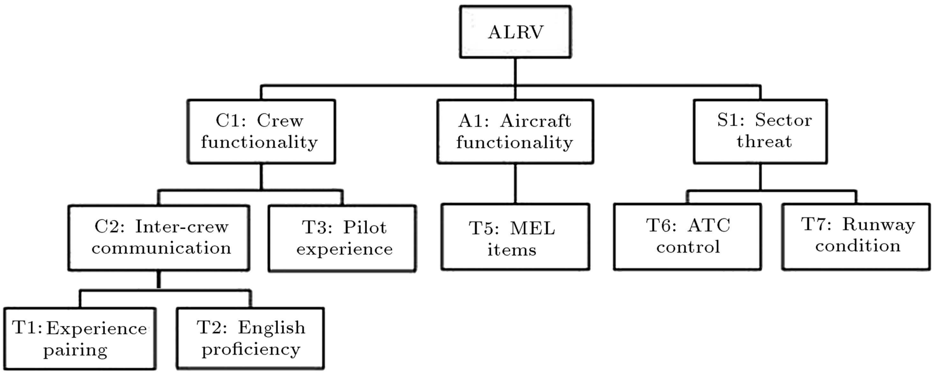

Figure 1. Example of risk model.

example in Figure 1, the approach and landing risk is a consequence of crew functionality risk, aircraft functionality risk, and sector threat risk. Similarly, crew risk is caused by inter-crew communication risk, experience risk, and stress risk. This hierarchical and causal structure has also been used by Kangari and Riggs [11], Tah and Carr [12], and Carr and Tah [13] for the expression of risk in the construction industry, and by Carreno and Jani [14] for insurance risk assessment.

2.1. Hierarchical structure of FORAS

The decomposition of a conceptual risk to its causal risks results in a tree structure, as illustrated in Figure 1. By the terminology used in a tree structure, each risk is defined as a node in the tree, and the risks decomposed from a risk are called child nodes of their upper level risk, while a node is called the parent to its child nodes. Taking the risk model in Figure 1 as an example, crew functionality risk is the parent node of inter-crew communication risk, experience risk, and stress risk, while these risks are the child nodes of crew functionality risk. Nodes without any child node are called leaves, and are referred to as risk factors of the model. The node at the top of the tree, which has no parent, is called the root node, e.g. the approaching and landing risk in Figure 1. In this paper, we term all the conceptual risks between the leaves and root as risk components.

The decomposition of risks is based on the domain experts' knowledge. The causal relation between child nodes and their parent node is also defined by experts and is expressed by rules. The rule is used to describe the degree of the resulting risk under various conditions of its causes, and such conditions are assessed in a linguistic manner. For example, the causal relation between experience pairing (T1), English proficiency (T2) and inter-crew communication (C2) can be formulated by the following rules:

- If T1 is low and T2 is low, then C2 is 1;
- If T1 is low and T2 is high, then C2 is 4;
- If T1 is high and T2 is low, then C2 is 6;
- If T1 is high and T2 is high, then C2 is 10.

The above rules together describe the assessment of the inter-crew communication risk under different conditions of experience pairing and English proficiency. The risk degree ranges from 1 to 10, and the greater the number, the higher is the risk. The formulation of the rules is based on experts' knowledge and is a result of group decision making. In this group decision making process, a work group is formed to interview pilots, safety managers, dispatchers and maintenance engineers and the risk factors that contribute to the concerned risk are discussed. Brain storming sessions are conducted to identify the most relevant factors which determine the concerned risk, followed by conference meetings to formulate the membership functions associated with all factors and the rules to describe the relationships among these risk factors.

The assessment of conditions in a linguistic manner alleviates the difficulty of quantifying uncertain judgment. This rule format, together with the procedure to draw a conclusion from the set of rules, is a special type of fuzzy inference system, called the Sugeno fuzzy inference system [15]. The Sugeno fuzzy inference system differs from other types of fuzzy systems in the consequence part. Many fuzzy inference systems, such as the Mamdani system, adopt linguistic expressions in the consequence, which requires a defuzzification procedure in the inference and suffers from some intrinsic defects of the defuzzification methods. The use of real numbers in the consequence by the Sugeno system avoids such a problem and improves computational efficiency in the inference procedure.

An alternative presentation of the above exemplified fuzzy inference system is to put it in a table format, as shown in Table 1.

Each risk and its causal risks in the FORAS model represent a fuzzy inference system. The number of rules in a fuzzy inference system is varied for each risk component, depending on how many linguistic terms are used to assess a causal risk. In the FORAS developed by Hadjimichael and his co-workers [7-9], the inference

Table 1. Table format of a fuzzy inference system.

C2:		**T2**	
		Low	High
T1	Low	1	4
	High	6	10

procedure was achieved using Fuzzy CLIPS [16]. In this study, we adopt a different inference procedure based on approximate reasoning. The Sugeno fuzzy inference system and approximate reasoning are discussed next.

2.2. Fuzzy inference systems

A Sugeno fuzzy inference system consists of a set of fuzzy rules in the following format:

$$\text{Rule } j: \text{ If } x_1 \text{ is } L_{1j},\ x_2 \text{ is } L_{2j}, ..., \text{and } x_p \text{ is } L_{pj},$$

$$\text{then } y = c_j,\ j = 1, ..., m, \tag{1}$$

where x_i, $i = 1, ..., p$, are the input variables to the system, L_{ij} is a linguistic term to describe the condition of x_i, such as *low*, *high*, *small*, or *large*, y denotes the output of the system, and c_j is the consequence of the rule. The consequence, c_j, is a crisp real number and, in this study, it indicates the resulting risk value from the given conditions.

The use of linguistic terms in fuzzy rules waives the requirement of precise assessment of conditions in traditional rules, and enables experts to express their uncertainty of judgment. Linguistic terms are qualitative descriptions of the input variable and are treated as fuzzy sets for quantification purposes. Fuzzy set theory [17] directly addresses the limitation of the sharp boundaries found in classical set theory and, hence, fuzzy sets are well suited to quantify linguistic terms. A fuzzy set is defined by a membership function that maps objects in a domain of concern to their membership value in the set. The degree of membership in a set is expressed as a smooth and gradual transition from 0 to 1. Such a smooth transition yields fuzzy set flexibility in modeling linguistic expressions and is more robust when dealing with imprecise judgment.

In the fuzzy inference system, when inputs are given, multiple rules are activated at the same time with different degrees of firing strength. The concluding value (i.e. output) of the system is synthesized from all the rules, based on approximate reasoning [17]. The firing strength of each rule is determined by applying a fuzzy conjunction of individual conditions in the rule. Such a conjunction is defined by a t-norm operator, $\otimes$. Let $\mu_{L_{ij}}(x_i)$ denote the membership function of x_i defined for linguistic term, L_{ij}, in the j-th rule, the firing strength of rule j is defined as:

$$z_j = \mu_{L_{1j}}(x_1) \otimes ... \otimes \mu_{L_{ij}}(x_i) \otimes ... \otimes \mu_{L_{pj}}(x_p). \tag{2}$$

In a Sugeno fuzzy inference system, the algebraic product is generally assigned to the operation of a t-norm, and, hence, Eq. (2) becomes:

$$z_j = \Pi_{i=1}^{p} \mu_{L_{ij}}(x_i). \tag{3}$$

The conclusion of the j-th rule is also defined by a t-norm operation, as $z_j \otimes c_j$, and is obtained as $z_j c_j$ when the algebraic product is used. The synthesis of the conclusions from all rules is obtained by a disjunction (an s-norm) operator:

$$y = z_1 c_1 \oplus ... \oplus z_j c_j \oplus ... \oplus z_m c_m. \tag{4}$$

A weighted average is used for the s-norm operator, and the conclusion or the output of the fuzzy inference system is obtained as:

$$y = \frac{\sum_{j=1}^{m} z_j c_j}{\sum_{j=1}^{m} w_j}. \tag{5}$$

2.3. Computation framework of FORAS

The model of FORAS contains many fuzzy inference systems, and the output of a fuzzy inference system is the input of another fuzzy inference system at the upper level. Such information computation feeds forward from the bottom of the tree to the top, until the concerned risk assessment is obtained at the root of the tree. An exception occurs at the node which combines the risks associated with multiple crews. Such a node is named an aggregate node in our study.

Consider the example in Figure 1, in which experience risk is an aggregate node combining the experience risks associated with multiple crews. The aggregated experience risk then serves as an input to the computation of crew functionality risk. The procedure of computing each crew's experience risk is identical, i.e. the sub-tree below the experience risk node.

The aggregation of individual risks is to place a weight on the chief pilot, called the Person In Charge (PIC), and a weight on the remainder of the pilots in the cockpit, and then to perform a weighted average operation on their risks. The rationale behind this weighting is that PIC generally has more decision power over other pilots in the cockpit. This weighted average is defined by the following equation:

$$r_a = \frac{w_p r_p + w_c \left(\frac{\sum_{i=1}^{n} r_i}{n} \right)}{w_p + w_c}, \tag{6}$$

where r_a is the aggregate risk; r_p is the risk; associated with the PIC; r_i, $i = 1, ..., n$, is the risk associated with the i-th pilot; n is the total number of pilots, excluding the PIC; and w_p and w_c are the weights of the PIC and the rest of the pilots, respectively.

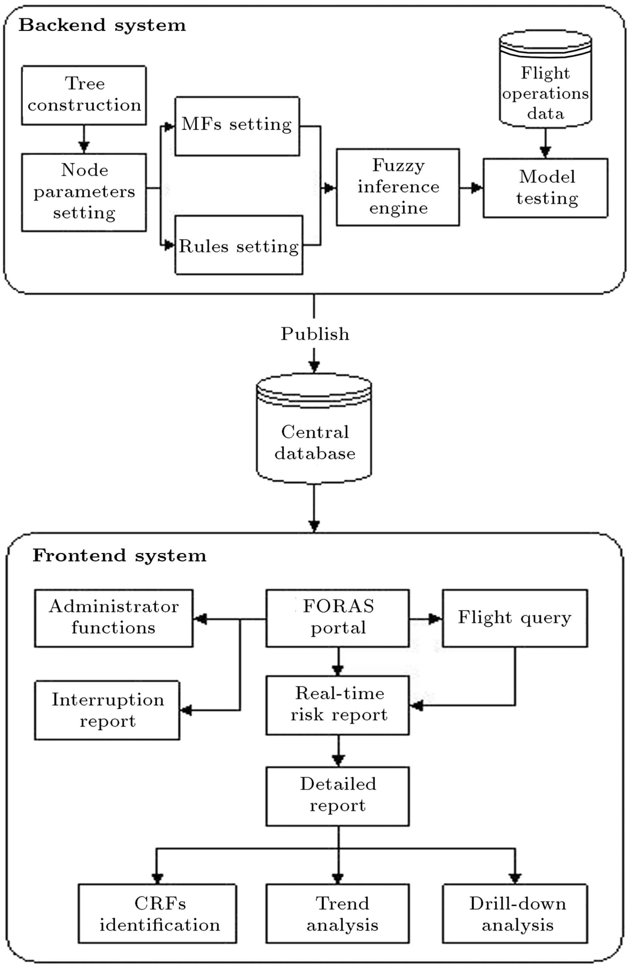

Figure 2. FORAS system architecture.

3. System architecture and implementation

The proposed FORAS has been implemented for an airline company. The purposes of this implementation are to provide a user-friendly interface for the safety manager to construct and maintain the model, establish a web-based system for online reporting, and analyze the risk assessment of each flight. Our system consists of a backend system for risk modeling and a frontend system for online reporting, as shown in Figure 2.

3.1. Backend system

The backend system provides a graphic and user-friendly interface for the safety manager to construct the FORAS tree model, as shown in Figure 3. Each node in the tree is associated with a set of parameters that specifies the node's characteristics. Such information will be used in online reporting and analysis of risk assessments. Parameters of a node include the data range of the node, invalid conditions, dispatching, and missing data. The data range of a node specifies the lower and the upper limits of the node, which are used to form the data display range

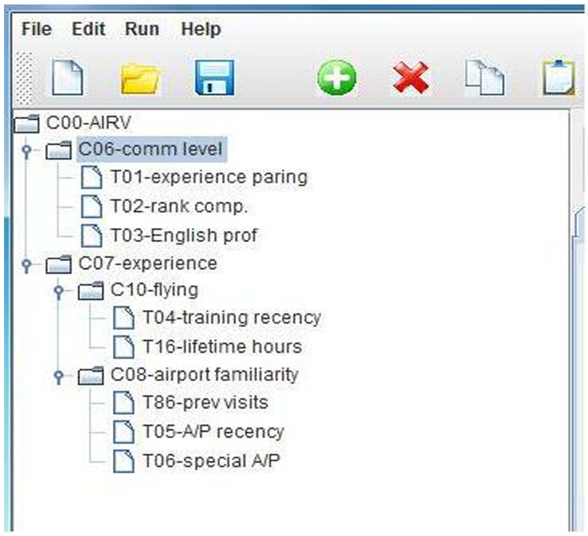

Figure 3. Tree model construction interface.

of this node and to constrain the search space when a change in this node is requested by the dispatcher. If the value of a node is constrained by an aviation regulation, the invalid condition parameter allows the user to specify the range beyond which the value is invalid. This information is also used in online flight risk assessment to single out any invalid operation. The dispatching parameter indicates if a risk factor is controllable. A risk factor is said to be controllable if it is related to crews or aircraft dispatch, and is uncontrollable if it is related to weather. The setting of this parameter is to provide assistant information when a dispatch change is considered. Missing data is sometimes inevitable in a database. If a node is critical in computing the flight's risk, the missing data option will be set as unacceptable, and the online risk computation of this flight will be interrupted. By contrast, if missing data is acceptable, a default value is set for this node and, therefore, the risk computation can continue.

As presented in the previous section, a node and its child nodes represent a fuzzy inference system that is expressed by a set of rules. It is necessary to set the membership functions for all child nodes in the fuzzy inference system. Figure 4 demonstrates the membership function setting screen of a node. The user can specify the number of membership functions associated with the node, the type of each membership function, and the parametric values of this membership function.

After the membership functions have been defined for all child nodes in a fuzzy inference system, a rule setting module will automatically catch these membership functions and arrange a corresponding rule setting layout for the user to define the consequence of each rule. The setting of rules can be done in either a rule format or a table format, as the example illustrats in Figure 5, where T01, T02, and T03 are the three linguistic variables, and C06 is the consequence of the fuzzy inference system. Figure 5 shows the set of rules and the corresponding rule table, given that the linguistic level of T03 is low. In this example, there are 27 rules to describe the causal relations between theses nodes. Figure 5 presents only part of the rules under the condition that T03 is low. By clicking on the tabs, "T03-Median" and "T03-High", it will show the rules under the conditions of "T03 is median" and "T03 is high", respectively.

After the model and its associated fuzzy inference systems are appropriately established, a trial computation function will automatically generate input fields

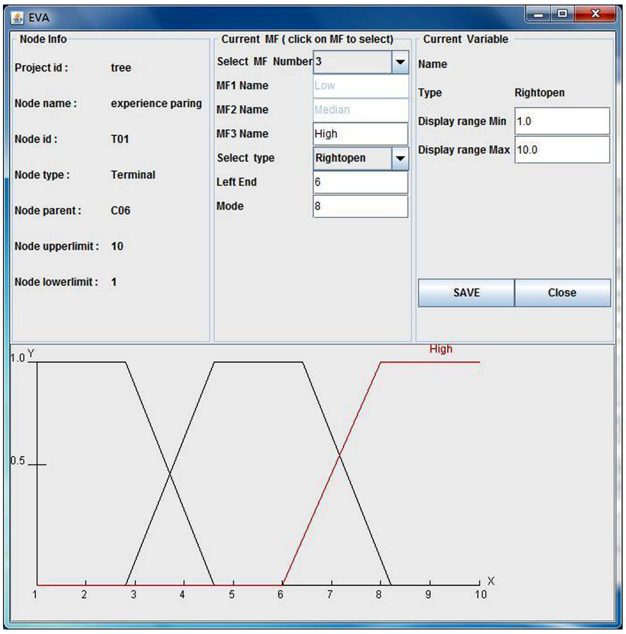

Figure 4. Membership function setting module.

based on the tree structure in MS Excel format. Data can be manually input or imported from a file. The user can compute the risk value at any selected node in the tree model.

3.2. Frontend system

After the FORAS tree model is built at the backend system, it is published to a central database. The frontend system then retrieves the model and its associated parameter settings from the database to compute the risk value of a flight. The risk assessment of a flight is computed two hours before its take-off. A snapshot of the online risk report of flights is shown in Figure 6, with the definitions of all acronyms appearing in the figure. The information associated with a flight includes the risk statuses in terms of the departure risk (DRV) and the approach and landing risks (ALRV) expressed by traffic lights, flight number, craft number, fleet number, departure time, departure airport, arrival airport, region of the flight, and finally, the risk values of departure operations and approach, and landing operations, respectively. If it is demanded, the user can click on the flight to check a detailed risk report, which lists the risk values of all nodes in the tree model associated with the flight (Figure 7). Clicking on the tab "Tree" in Figure 7 will show the entire tree model and the risk values associated with all nodes. The input values of all nodes can also be seen by clicking on the tab "T Value".

In the detailed report panel, there are extended functions to further analyze the flight's risk. The tab, "Trend Analysis", in Figure 7 compares the flight's risk with the historical risk records of the same flight, fleet, or region by using a control chart, as shown in Figure 8, where the upper and lower control limits are the ± 3-standard-deviation of historical risk values. A drill-

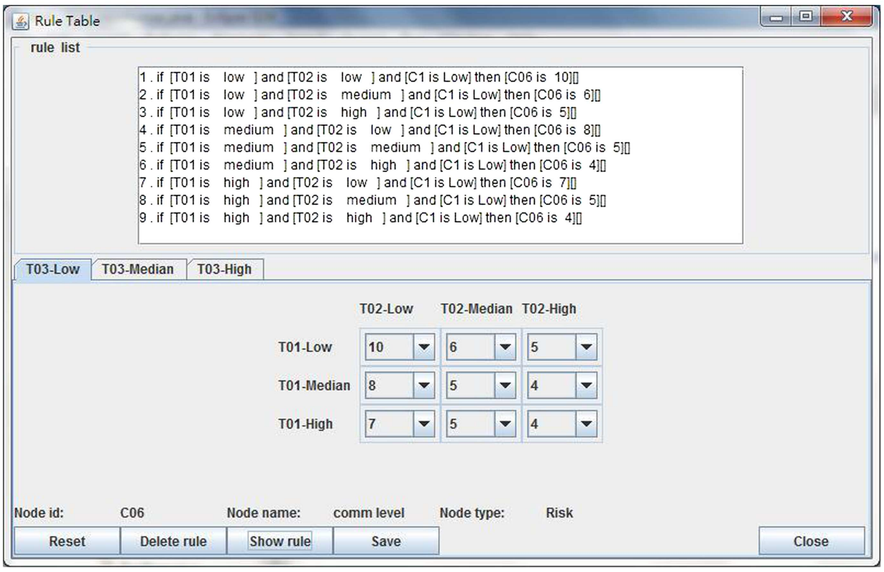

Figure 5. Rule setting module.

Flight List

Normal · Warning · Alert · Data Incomplete · Beyond Limits · Interrupted · Processing

DRV	ALRV	Flt No	A/C No.	Fleet	Dep. Time(TPE)	DEP A/P	ARR A/P	Region	DRV	ALRV
		BR31	B16716	B777	2011/09/23 20:00	ANC	TPE	THM	1.00	1.00
		BR68	B16715	B777	2011/09/23 17:25	BKK	TPE	THM	1.00	1.00
		BR772	B16301	A330	2011/09/23 14:15	TSA	SHA	THM	1.00	1.15
		BR855	B16405	B747	2011/09/23 14:10	TPE	HKG	THM	1.00	1.00
		BR392	B16701	B777	2011/09/23 13:55	SGN	TPE	THM	1.00	1.00
		BR67	B16717	B777	2011/09/23 13:50	BKK	LHR	EUR	1.00	1.00
		BR868	B16410	B747	2011/09/23 13:45	HKG	TPE	THM	1.00	1.22
		BR35	B16711	B777	2011/09/23 13:30	YYZ	TPE	THM	1.22	1.00

DRV: Departure Risk Value; ALRV: Approach and handing risk value; Flt no: Flight number; A/C no: Aircraft number; Fleet: The fleet that the flight belongs to; Dep. time: Departure time; Dep A/P: Departure airport; ARR A/P: Arrival airport; Region: The region the flight belongs to.

Figure 6. Risk assessment report.

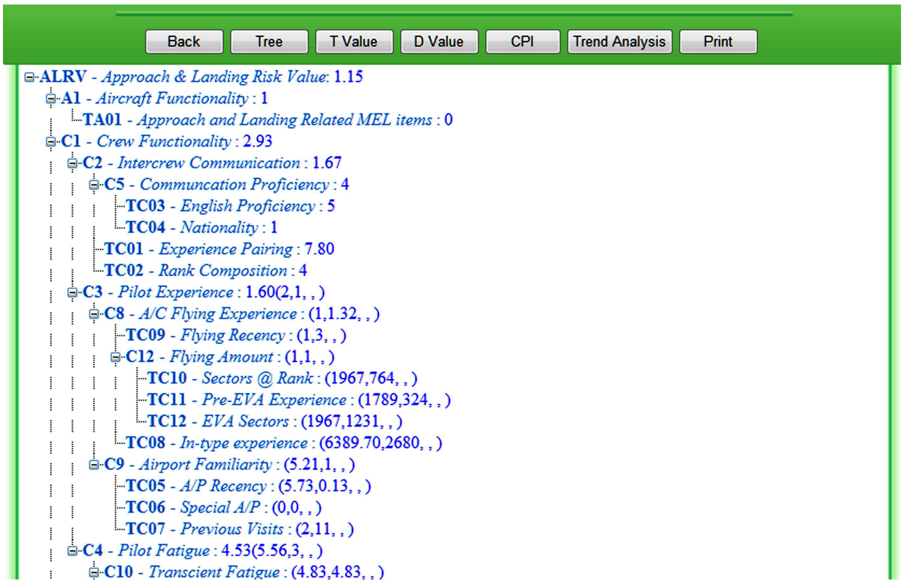

Figure 7. Detailed risk assessment report.

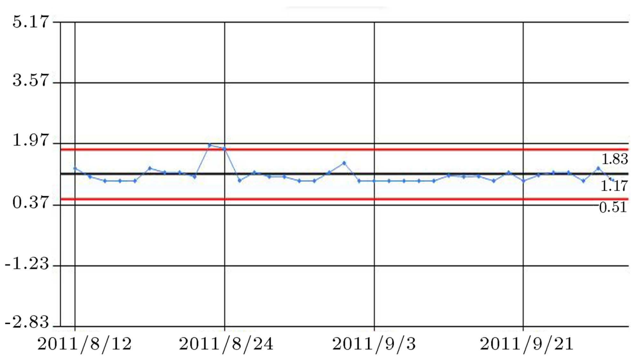

Figure 8. Risk value trend analysis.

down analysis is also provided by clicking on the risk factors of the tree (tab “D Value”).

When the risk of a flight is assessed to be too high, it is necessary to adjust the flight's operations. When such a high risk occurs, it is critical to identify the risk factors most contributing to the risk concerned, and find suitable changes for these risk factors to mitigate flight risk. The tab “CPI” in Figure 7 links to such a function. The dispatcher can rearrange the operations based on this information. The algorithms to identify critical risk factors will be discussed in Section 4. In the critical factor identification module, we also provide a trial computation function for the user to check the resulting risk assessment of a flight after possible changes are made for risk factors. When the changes to the dispatch are confirmed, the dispatcher will trigger a recalculation function that retrieves data from the database and re-computes the risk assessment of the flight.

Other functions provided by the frontend system include flight queries, an interruption report that summarizes exceptional events during processing, and an administrator function for the system administrator to set up operational parameters, such as user authority, time to update the control chart, etc.

4. Critical risk factor identification

4.1. Critical risk factor identification; Algorithm I

Critical risk factors are those factors that are highly causal to the assessment. Hadjimichael [7] suggested three possible definitions of critical risk factors, including the greatest contributors to risk assessment, most deviating from baseline values, and most sensitive input parameters. According to discussions with the case airline company, the third definition of Hadjimichael [7] is adopted and implemented by finding the factors providing the greatest marginal reduction of global risk within the entire model. Individual risk factors are changed one by one to reevaluate the risk of a flight, and those risk factors having greater marginal effect than the others are considered more critical. This concept is formalized by the following equation:

$$i^* = \underset{i}{\operatorname{argmax}} \left\{ \left| \frac{\partial r_{\text{root}}}{\partial f_i} \right| \right\}, \tag{7}$$

where r_{root} is the risk function of the root node, and f_i is the i-th risk factor. We consider the absolute derivative in Eq. (7) because the increment of a risk factor can increase or reduce the risk value at the root node. Based on directions, they change the risk value of the root node. We classify risk factors into three distinct sets, namely, the-Larger-the-Better (LB), the-Smaller-the-Better (SB), and Nominal (N). An increment of a risk factor in the LB set will reduce the risk value of the root node, while it will increase the risk by a risk factor in the SB set. A risk factor is said to be nominal if it takes attribute values only.

By excluding f_{i^*} from the list and utilizing Eq. (7) again, we can find a few critical risk factors. However, since r_{root} does not have an explicit functional form, direct use of Eq. (7) is impossible. Instead, the following algorithm is used to approximate this equation:

CRFI Algorithm I:

For $i = 1, ..., n$ /* n risk factors in total*/

Case

$f_i \in$ LB

$$d_i = -\frac{r_{\text{root}}(f_1, ..., f_i + \Delta f_i, ..., f_n) - r_{\text{root}}(f_1, ..., f_i ..., f_n)}{\Delta f_i};$$

$f_i \in$ SB

$$d_i = -\frac{r_{\text{root}}(f_1, ..., f_i - \Delta f_i, ..., f_n) - r_{\text{root}}(f_1, ..., f_i, ..., f_n)}{\Delta f_i};$$

$f_i \in$ N

$$d_i = -\left[r_{\text{root}}(f_1, ..., f_i^*, ..., f_n) - r_{\text{root}}(f_1, ..., f_i, ..., f_n) \right];$$

EndCase

Next i;

Rank $f_i, \forall i$.

In the algorithm, d_i is used to approximate the derivative in Eq. (7) for different cases of risk factor, where Δf_i is a very small deviation from f_i and is defined as:

$$\Delta f_i = \{\max(f_i) - \min(f_i)\} .k,$$

where k is a small ratio. In the case of nominal risk factor, its ideal attribute (f_i^*), where the risk value of the root node is minimized by this factor, is used as a proxy of the margin of the risk factor.

The above algorithm represents a reasonable inference procedure of critical risk factors, based on the sensitivity of a factor. However, it does not perform well, due to the insensitive nature of the fuzzy membership functions. Considering the membership functions example in Figure 5, when the value of this node changes from 9 to 8, the output of the membership function, *high*, remains the same. As a result, the conclusion of its associated fuzzy inference system is unchanged; so does the risk value at the root node. When most risk factors fall within similar intervals, CRFI Algorithm I will fail. Another disadvantage of this algorithm is its intensive computation requirement. The root node's risk value needs to be computed n times with respect to the change in each risk factor. Thus, an alternative algorithm is developed to alleviate the computational burden and find critical risk factors where the risk model is less sensitive to changes in risk factors.

4.2. Critical risk factor identification; Algorithm II

To avoid the problem of insensitivity of membership functions, this algorithm varies the value of a node with a wider margin, which is big enough to alter the global risk value. When the risk value at the root node is assessed as too high, the dispatcher will seek the changes of some operations to mitigate the risk to a safety level. This safety level is called a target risk value, denoted by r_t, which is usually set as the average risk value of normal flights. The idea of this algorithm is to trace along the tree from the root node to leaf nodes, i.e. risk factors, and find the changes needed at those nodes to reduce the root node risk to the target value. The method is to find the desired risk levels of the child nodes, so that the root node can reach the target risk value, and such a procedure repeats until reaching the leaf nodes. In this manner, the desired values of a set of risk factors are obtained and factors in such a set are considered as critical risk factors. The algorithm is presented below, where a back-trace subroutine, denoted by BT (*node*, *target*), is to find the desired values of the child-nodes of node, so that the risk value of node is reduced to target. The notations used in Section 2 to describe the fuzzy inference system are also used here.

CRFI Algorithm II:

```
Main()
    Call BT (root, r_t) /*root denotes the root
     node */
    Record x_i^* /* desired values of node i, ∀i*/
    Recalculate the risk of root with x_i^*, ∀i
BT(node, target)
    If node ∉ Leaf /*Leaf is the set of all leaf
    nodes */
        j^* = arg min_i {|c_j(node − target)|}
        /*c_j(node) :
        the j-th rule of node*/
        If z_j^* < 1
            For i ∈ Child (node) /*Child(node) :
            set of child-node of node */
                If μ_{L_{ij*}}(x_i) < 1
                    Case
                        i ∈ LB
                            x_i^* = min {x_i | μ_{L_{ij*}}(x_i) = 1}
                        i ∈ SB
                            x_i^* = max {x_i | μ_{L_{ij*}}(x_i) = 1}
                        i ∈ N
                            x_i^* = x_i^opt /*x_i^opt
                            is the ideal value of x_i^*/
                    EndCase
                    Call BT(i, x_i^*)
                EndIF
            Next i
        EndIf
        Return
    EndIf
    Return
```

The main algorithm passes the root node index, *root*, and its target risk value, r_t, to the back-trace algorithm, BT. After receiving the desired values of risk factors from the back-trace algorithm, the overall risk value is re-computed. In the back-trace algorithm, the consequences of all rules associated with the current node are compared with the target risk value. The idea is to find the rule having a consequence most close to the target value, and find the input hindering full activation of this rule. The desired value of the identified input is determined to improve the activation of the rule.

Let c_j (*node*) denote the consequence of the j-th rule of the current. The rule that has a consequence most close to the target value is identified as, j^*. If the identified rule is not fully activated, i.e. $z_{j^*} < 1$, it means there is room to change the inputs, i.e. its child nodes, with the premise to increase this rule's activation degree. Only if the input does not have a full membership of its linguistic term (i.e. it still has room to improve), will the change be made on this input variable. The change is made according to the type of input variable, and the magnitude of change is the minimum amount required to obtain full membership of this input on the linguistic term. After the target values of the node's child nodes are determined, the back trace subroutine is executed again from these child nodes until reaching the leaf nodes. Finally, the target values are obtained for the critical risk factors via such a recursive manner.

5. Computational result analysis

The case study airline company has established a FORAS tree model for assessing approaching and landing risks. The model consists of 39 risk components and 53 risk factors. The construction of the tree model and its associated parameters are obtained through a group decision making process, in the form of brain storming sessions and conferences. The participants include pilots, safety mangers, maintenance technicians and dispatchers. To evaluate the performance of the FORAS model, two experiments are conducted, based on real flight operation data of the airline company.

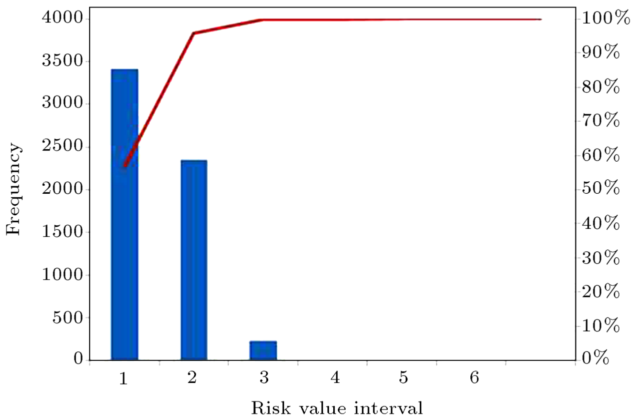

Figure 9. Distribution of risk values.

The first experiment is to evaluate model validation by comparing the risk assessments of a flight by the model and by the experts, respectively. The second experiment evaluates the performance of the proposed critical risk factor identification algorithms.

5.1. *Validation of FORAS model*

The FORAS presented in this paper was implemented online by the case study airline company in January 2012, to assess the ALR operations risks of all flights. The statistics of the assessment results of the flights from January 2012 to February 2012 (6010 flights in total) are summarized as follows: Mean risk value is 1.17 with standard deviation as 0.35. The minimum risk value is 1.00 and the maximum is 6.00. Distribution of the assessed risk values is depicted in Figure 9 in which the ALR values of more than 99.7% of the flights were less than 3. Thus, we define the flight with a risk value less than 3 as being within a safety range.

Each flight assessed to have a higher risk, i.e. greater than or equal to 3, was carefully checked by the safety managers. The safety managers of the case study company confirmed the appropriateness of the assessed results by FORAS, and identified the causes of the high risks of these flights. The operations of these flights were adjusted until they were assessed to be normal by FORAS. Flights assessed to be normal (i.e. risk value less than 3) are also randomly picked by safety managers to check the appropriateness of their assessed results. Safety managers did not find any flight that was assessed to be normal, but, in fact, contained factors leading to high risk.

5.2. *Performance evaluation of critical risk factor identification algorithms*

In testing the CRFI Algorithm I presented in Section 4.1, we often failed to find any critical risk factor due to the insensitivity of membership functions, as discussed earlier, and the algorithm generally took around 60 seconds (by a PC with an Intel® Core(TM)2 Duo CPU E8400 @ 3.00 GHz and 1.96 GB RAM) to complete the computations for a single flight. Thus, CRFI Algorithm I was discarded. CRFI Algorithm II, on the other hand, can always find critical risk factors, and its computational time is 0.402 seconds per flight, on average. However, CRFI Algorithm II is a heuristic that greedily searches the branch to provide a rapid improvement on overall risk, but it ignores other branches that may potentially provide greater marginal improvement of the risk. To evaluate the performance of CRFI Algorithm II, the algorithm is compared with a Genetic Algorithm (GA), which globally searches the entire set of risk factors in the tree.

In this genetic algorithm, the desired values of risk factors are encoded as a string consisting of all risk factors. The fitness function is defined as minimization of the difference between overall risk and the target risk value. Reproduction of chromosomes is carried out by tournament selection. The single point crossover is used to obtain new chromosomes by swapping genes between two chromosomes with a crossover rate 0.8, while a mutation operation randomly picks and alters the value of a gene with a mutation rate of 0.05.

Thirty flight records, which were assessed by FORAS as having relatively high risks, are used in this experiment. CRFI Algorithm II and the genetic algorithm were executed on 30 flight records to identify their critical risk factors, and the results are shown in Table 2 (both algorithms were tested with a PC with Intel® Core (TM)2 Duo CPU @3.00 GHz & 1.96 GB RAM). In this experiment, the target risk value is set as 2.00. Table 2 shows that the proposed CRFI Algorithm II can always find critical risk factors and alter their values to reach the target risk. The genetic algorithm demonstrates a similar effectiveness. However, its computational time (48.086 seconds on average) is much greater than that of the CRFI Algorithm II (0.402 seconds on average). This computational result confirms the effectiveness and efficiency of the CRFI Algorithm II in identifying the critical risk factors of flights.

6. Conclusions

In this study, we have presented the implementation of a FORAS system for an airline company. The system can assist the safety manager in constructing risk models, and establishes a platform for real-time risk assessment and online data analysis. The system focuses on the causal factors of the operational risk of a flight, and provides tools for identifying critical risk factors of the flight. Such information is useful as a proactive risk reduction and dispatch decision support system. An approach and landing risk model has been constructed by employing the FORAS system. Experiments based on practical data have been conducted for FORAS model validation and

Table 2. Computational results by CRFI II and genetic algorithm, respectively.

Flight	Initial risk	CRFI II		GA	
		New risk	Time# (sec)	New risk	Time# (sec)
1	4.80	2.00	0.588	2.00	24.733
2	5.00	2.00	0.085	2.00	45.623
3	3.00	2.00	0.396	2.00	52.653
4	4.49	2.00	0.523	2.01	72.496
5	6.47	2.00	0.391	2.00	55.493
6	4.95	2.00	0.487	2.00	56.828
7	3.00	2.00	0.114	2.00	28.092
8	3.85	2.00	0.393	2.00	68.471
9	4.91	2.00	0.438	2.00	45.927
10	5.55	2.00	0.451	2.00	27.582
11	3.00	2.00	0.089	2.00	56.539
12	4.15	2.00	0.68	2.00	57.456
13	4.11	2.00	0.202	2.00	39.682
14	5.37	2.00	0.185	2.00	46.127
15	4.22	2.00	0.612	2.00	61.344
16	4.60	2.00	0.413	2.00	53.749
17	2.68	2.00	0.529	2.00	37.862
18	4.11	2.00	0.468	2.00	53.857
19	6.00	2.00	0.42	2.00	43.056
20	3.11	2.00	0.649	2.00	45.650
21	4.14	2.00	0.201	2.01	70.231
22	5.89	2.00	0.508	2.00	22.788
23	4.00	2.00	0.139	2.00	30.980
24	4.00	2.00	0.068	2.00	48.566
25	5.45	2.00	0.499	2.02	68.126
26	6.00	2.00	0.494	2.00	50.420
27	2.98	2.00	0.494	2.00	39.509
28	3.58	2.00	0.413	2.04	71.027
29	6.67	2.00	0.629	2.00	23.584
30	6.00	2.00	0.509	2.00	44.140
Average	4.54	2.00	0.402	2.00	48.086

#: The computation was done by a PC with Intel® Core(TM)2 Duo CPU @3.00 GHz & 1.96 GB RAM.

performance evaluation of the proposed critical risk factor identification algorithms.

The performance of a FORAS system heavily relies on the appropriateness of the risk model. The decomposition of risk components into a tree structure, and the parameter settings of fuzzy inference systems associated with the risk model, require an efficient knowledge elicitation from domain experts. This process is generally time-consuming, in which losing focus on the subject is easy, and important factors are difficult to be clarifed due to problem complexity; it is also likely to be dominated by opinion leaders. The exploration of group decision making theories and techniques would help improve the efficiency of this knowledge elicitation process. Our future research will focus on the formulation of group decision making procedures for FORAS risk model construction.

The development of a FORAS system may not be an easy task for small sized airline companies. A cloud computing architecture managed by a third party foundation can provide easy access and modeling for such users. In our future research, we will also study the implementation of FORAS on a cloud computing platform, and the formulation of an XML standard for model communication. Though most factors and parameter settings in the risk model of the case company are generally universal in the airline industry, some still need to be customized by individual airlines. The cloud-based system will also provide a friendly interface for users to change the parameters online.

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