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# Integration of human factors in project uncertainty management, a decision support system based on fuzzy logic\*

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**ABSTRACT:** Decision-making under uncertainty implies dealing with information about different choices and their consequences that is partial for the decision-maker. In front of uncertainty, either the decision can be postponed, waiting for complementary information or the decision can be only made on the available information, despite possible consequences on the decision. We propose a model to identify and structure needed information. Human factors are taken into consideration in this structure. Then, to process the collected information, we propose a Fuzzy Decision Support System (FDSS) which deals with uncertain information. In this approach, a sequence of decisions leads to a final choice, taking progressively into account new information whose role is to refine available information. Human representation and reasoning mode are imitated, respectively by fuzzy sets and fuzzy inference rules. We apply the proposed FDSS to a case study held on a ski resort. The results with this approach prove effective compared to those a naive decisional approach.

## 1 INTRODUCTION

Project management involves making decisions in a context of uncertainty. These decisions result from some inference rules on some quantitative or qualitative variables, with usually uncertain values that come from different sources and could become progressively complete and precise. Generally, it is only at the end of the project that precise and accurate values of most variables are available. However, a project manager has to make decision, throughout the different phases to make the project evolves, even if the information is uncertain or the inference rules are not strict. It might be difficult to process all the uncertain information and alarm signals in the decision-making process. In such circumstances, usually the decision-maker adopts a reductive approach to make a decision only based on the piece of information that is available and looks more important. In doing so, the risk is that the decision is made without some crucial information. We propose a FDSS that takes into account both quantitative and qualitative variables and

tolerates the lack or imprecision of information. In this approach, the requested information is first identified and structured, then a sequence of decisions leads to a final choice, taking progressively into account new information. Human representation, and reasoning mode are modeled by fuzzy sets and fuzzy inference rules (Zadeh 1965). The structure of this paper is as follows. In section 2, we propose a definition of uncertainty and explain how this vision of uncertainty leads us to structure information so that it takes into account human factors. Section 3 details the mechanism of the proposed model. In section 4, an application case in ski is presented. The objective is to help a skier decide whether to change one's itinerary to avoid avalanches. In section 5, we discuss the results of the system and in section 6, we explain how it could be improved.

## 2 DECISION MAKING UNDER UNCERTAINTY

In order to better understand the decision-making process, we need to understand the notion of uncertainty (Klir 2005). Thus, in this section, decision-making under uncertainty is defined and some approaches to

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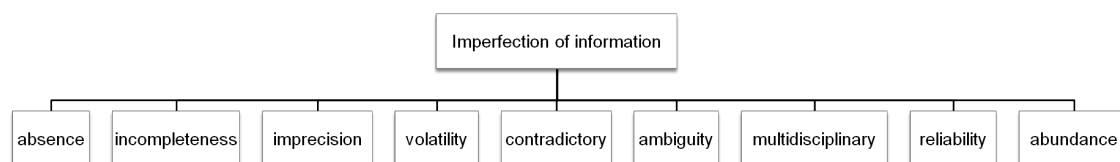


Figure 1: Typology of imperfection of information

cope with uncertainty are presented. Then, the human dimension is integrated in the definition and characterization of uncertainty.

## 2.1 Literature review

The decision-maker usually chooses an option based on a benefit/risk balance of the available options. The process involves selecting the best among several options through an evaluation of the parameters of each option and its consequences (Panneerselvam 2006). Decision theories study how this benefit/risk balance is calculated by the decision-maker. Simon criticized the implicit hypothesis of decision theories according to which the necessary information is always available (Simon 1969). In fact, the decision-maker does not always have the requested information at his disposal to make a decision. If he knows all the possible options and their consequences, he is in the case of a deterministic decision. In a non-deterministic case or decision under uncertainty, the information about different options and their consequences is imperfect for the decision-maker (Panneerselvam 2006). Before defining the imperfection of information, it should be noted that two concepts of information and uncertainty are strongly interconnected. Information has got to decrease uncertainty (Klir 2006). Imperfection is a property of information that does not eliminate uncertainty.

Several typologies of imperfection of information are described in Tacnet's thesis (Tacnet 2009). All of them consider uncertainty as a form of imperfection of information. We consider uncertainty as a result of the imperfection of information. In figure 1, we propose a typology of the different forms of imperfection of information that cause uncertainty. These forms are explained as follows. Absence: information is totally unavailable. Incompleteness: information is partial unavailable. Imprecise: existence of multiple and conflicting interpretations for the same information (Thiry 2002). Volatility: information can change rapidly. Contradictory: existence of paradoxical information. Ambiguity: existence of multiple information for the same variable. Multidisciplinary: information that concerns multiple domains. Reliability: information whose source is not reliable. Abundance: a great deal of information.

The degree of uncertainty can be different from a

decisional situation to another one. The degree of uncertainty would then correspond to the difference between requested information and available information to make a decision. Some authors (Thiry 2002) defined uncertainty *via* this difference. We consider it as the degree of uncertainty.

The previously mentioned Simon's critique, emphasizing the importance of the availability of information and human representation, up to that moment ignored by decision theories, leads decision theories to a new direction (Tsoukiàs 2008). The new approaches study and formalize decision, taking into account the imperfection of information that could correspond to human representation. The interval theory is one of the first formalization for imprecise information (Moore 1966). Fuzzy sets, established by Zadeh in 1965, offer a new perspective to process imprecision of human language (Tsoukiàs 2008). The fuzzy sets theory concerns the degree of membership of a set. To manipulate imperfect knowledge in a non-probabilistic frame, a possibility distribution of a proposition could be represented by a fuzzy set (Tacnet 2009). In this way, the possibility theory is developed (Zadeh 1978, Dubois and Prade 1988) to formalize the necessity and the possibility degree of an event. The counterfactual theory, developed by an American philosopher (Lewis 1973), proposes the relation of comparative possibility for two events, that expresses an event is more conform to what we know about the real world than another event (Dubois and Prade 2006). Psychological and philosophical theories, such as Simon and Lewis research works, offered a new vision to process uncertainty.

Even if information is available, cognitive psychology affirms that our ability to process information is restricted by the limit of our immediate memory that affects our judgment (Miller 1956). Therefore, to process a great deal of information or to cope with uncertainty, the human being needs to be helped by decision support systems that take into account uncertainty. However, as Simon outlines it, the human is at the center of a decision process (Tsoukiàs 2008) and the decision is influenced by his mental representation of the real world. For these reasons, in the next section, uncertainty is defined taking into account human dimension.

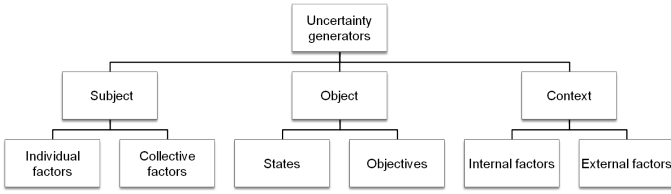


Figure 2: Typology of uncertainty generators

## 2.2 Human dimension in the characterization of uncertainty

In academic literature, we distinguish two main approaches to define uncertainty: the subjective and objective approaches. Objective approaches define uncertainty by emphasizing an object's state which is unknown and unsure. Subjective approaches define uncertainty by emphasizing mental states of the subject who is unsure. We consider that uncertainty is a relationship between a subject and an object. It is important to take both human factors and object properties (states) into account in the characterization of uncertainty. For these reasons, we propose the following definition of uncertainty: a subject's conscious lack of knowledge about an object, which is not yet clearly defined (or known), in a context requiring a decision (Hassanzadeh et al. 2010). Based on this definition, a typology for uncertainty generators is proposed in figure 2, which helps identify and classify generators of uncertainty in three classes: subject, object, and context. The subject class refers to human factors such as subject's psychological traits and professional experiences as individual factors, and to contradictory opinions and debates as collective factors. The object class refers to states of the object that are dynamic and could be changed and affect the objectives which depends on the object's states. The context class refers to internal environmental factors such as organizational and hierarchical elements, and to external environmental factors such as the circumstances of the decision. This vision allows us to take into account and control some of the generators of uncertainty, in order to reduce it as much as possible and deal with what remains according to the type of the generator. The proposed typology, as a basis of our model, helps organize variables that should be taken into account in decision-making under uncertainty.

## 3 MODEL

The purpose of this model is support decision under uncertainty, including three main elements: 1) input uncertain variables, 2) non-strict inference rules, and 3) decision modalities.

### 3.1 Organization of variables

In order to make a decision, variables which could affect our decision have to be identified. The proposed typology in section 2.2 gives the identified vari-

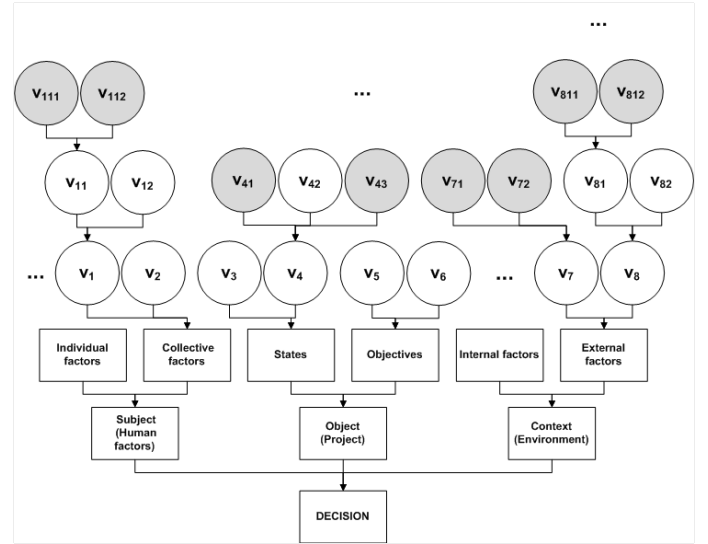


Figure 3: Example of a tree of the variables at the first phase of a project

ables a structure. Then, according to the project's objectives, different phases of the project are defined. The project's phases are marked by decision milestones that evaluate the obtained results at the end of each phase. In doing so, a sequence of decisions conducts to the final objectives. The list of available variables should be identified for each decisional milestone. Figure 3 shows the classification of the variables, at the first phase of a project, in a directed tree (a connected acyclic simple graph). The root of the tree symbolizes the decision of this phase. The rectangles symbolize the classes of the typology and are the generic variables for all projects. It should be noted that the classes of the typology are also considered as variables. The circles symbolize all the identified variables in this project. These variables specify the generic variables. For example, the variable Collective factors is specified by the variables  $v_1$  et  $v_2$ . Likewise, each variable could be specified by other variables and is connected to them by arcs (arrows):  $v_1$  is specified by  $v_{11}$  and  $v_{12}$ . The number of the variables and their positions change from one project to another. Both rectangles or circles are called nodes. A node is white if its value (information) is available, and grey if its value is not available. For example, here  $v_{11}$  and  $v_{12}$  are not yet available at this phase.

### 3.2 Characteristics of variables

A set of characteristics describes each variable in order to study its behavior and its impact on the decision. Some of these properties are as follows: name (identifier), type (quantitative, qualitative), unite (for quantitative variables), range (possible intervals for quantitative variables and different modalities for qualitative variables), state (static if it does not change or dynamic if it changes), source of information (that provides information. For example, experts, news, Internet), measurement instruments and methods (instrument or calculation methods for quantitative vari-

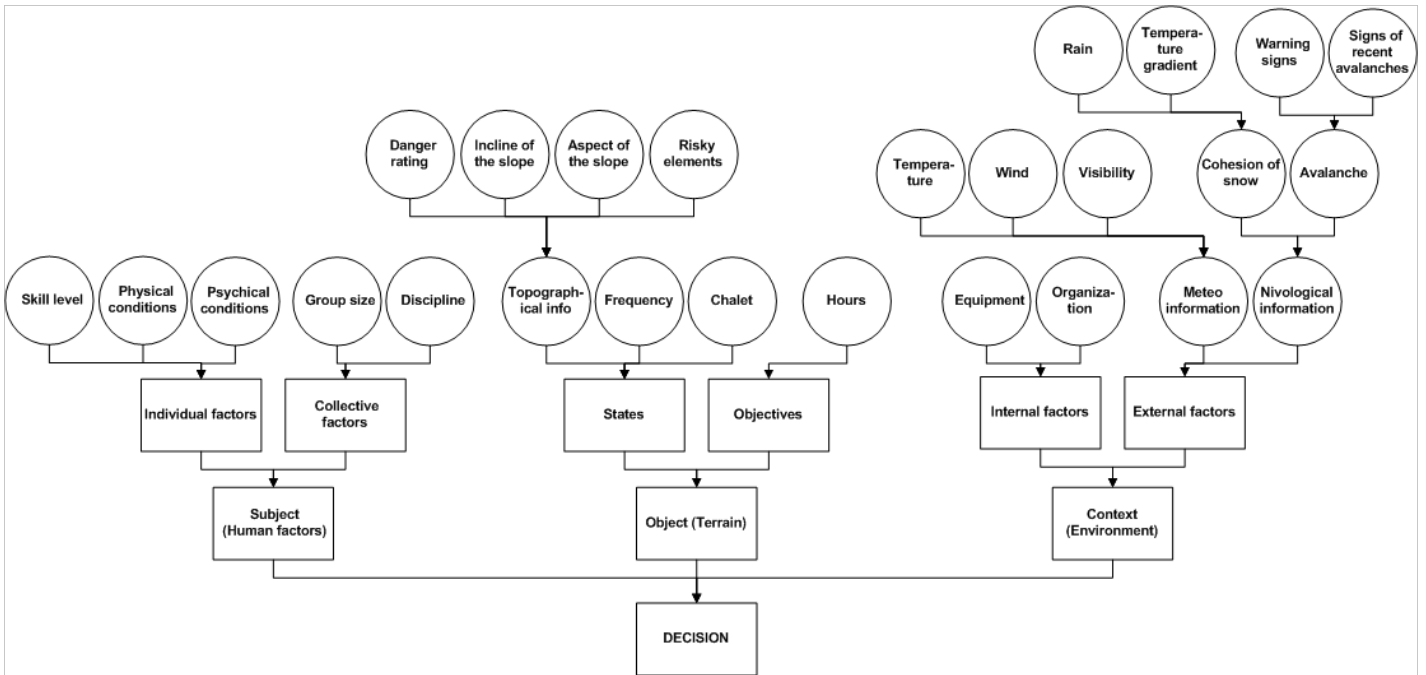


Figure 4: The tree of the variables at the last phase of the ski resort project

ables, and descriptive methods for qualitative variables, for example, observation, experimentation), and imperfection of information, illustrated in figure 1 (absent, incomplete, imprecise, volatile, contradictory, ambiguous, multidisciplinary, reliable, abundant). Table 1 of the section 4.2 gives two examples in application case.

### 3.3 Behavior of variables

The behavior of a variable refers to its availability in different phases of the project. In the tree (figure 3), the white and grey nodes respectively represent, available and unavailable variables at the first phase of the project. Grey nodes become white in the next phases, when their values become available. The total in-degree of a node (the number of entering nodes) illustrates how many variables are needed to know the exact value of a studied node (incoming node). The degree of uncertainty of a compound variable is calculated by the ratio of grey in-degree nodes/total in-degree and outlines the difference between requested information and available information to calculate the variable in a phase of project. For example, in figure 3 the degree of uncertainty of the variable  $v_4$  is  $\frac{1}{3}$ . We call elementary variables the leaf nodes (the nodes with the white in-degree equal to zero) and compound variables, the non-leaf nodes. In the context of project management, an elementary variable could have two behaviors. It could stay elementary until the end of the project, if it does not have any grey entering node (grey in-degree nodes equal to zero). It means that its value is not calculated from other variables, but it does not mean its value is precise and exact, it could be update in the next phases, when new information arrives. An elementary variable could become a compound in the next phases, if it has grey entering nodes (grey

in-degree nodes non zero). For example, in a studied phase, none of its entering variables is available, but we could have a general estimation of its value. Little by little, in the next phases, it could be possible to obtain or estimate the values of its grey entering nodes, thus they become white and the studied variable becomes a compound variable.

In a studied phase, hence grey variables are not available, decision is based on white variable. The number of the grey variables (unavailable variables) is useful to measure the degree of uncertainty.

### 3.4 Representation of variables

After the identification, the classification, and analysis of the variables' behavior, representation of their values is required to study their changes. Representation of variables in a formal language should allow to apply logic operators to calculate their impact on the decision. Human representation of each variable could be modeled by fuzzy sets that are not sharp-edged, contrary to classic sets whose borders are strict and do not allow an object to position at the border between two sets. For this reason, fuzzy sets are applied to model the impact of uncertain variables.

The value of each variable could be qualified by linguistic terms to express its impact on its incoming variable. The value of  $v$  (a number, an interval, or a modality) is qualified by a set of linguistic terms, such as  $A = \{a_1, \dots, a_i, \dots, a_n\}$ . These linguistic term can be represented by a fuzzy sets that could have imprecise borders with each other. For example, in figure 3, suppose that  $v_1$  is Collaboration factor that has an impact on its incoming variable Collective factors and the range of this factor is a note between 1 and 20. This note could be qualified by a set of linguistic terms such as  $A_1 = \{bad, average, good\}$ . Three

| Name             | Type         | Unite  | Range       | State  | Source                                    | Measurement             | Imperfection |
|------------------|--------------|--------|-------------|--------|---|-------------------------|--------------|
| Skill level      | qualitative  | none   | 3 levels    | static | group members                             | discussion, observation | incomplete   |
| Incline of slope | quantitative | degree | 4 intervals | static | map, photo, inclinometer, experimentation | descriptive methods     | imprecise    |

Table 1: Characteristics of variables

fuzzy membership functions represent these terms and divided the range of the values of the variable  $v_1$  into three subsets. Some values of  $v_1$  could be positioned at the border of several linguistic terms. For example, 7 is 60% bad, 40% average, and 0% good. It should be noted that the choice of these functions and fuzzy intervals depends on expert's judgment (Tacnet 2009).

### 3.5 Inference rules

To calculate the influence of the variables on the decision, the inference rules are created. The value of a compound variable  $v$  depends on the set of its elementary or compound entering variables:  $\{v_1, \dots, v_i, \dots, v_n\}$ ,  $1 \leq i \leq n$ . These entering variables do not have the same impact on  $v$  and are ordered according to the importance of the impact of each  $v_i$  on  $v$ . This importance order has to be taken into account to establish the inference rules. An average or a weighted average is not an adequate solution to calculate (Simon et al. 2007) the value of a compound variable. We use a fuzzy inference system (FIS) to calculate the value of  $v$  from the values of  $v_i$ . The value of each variable could be a number, an interval or a modality, but it is qualified by a linguistic term that corresponds to human perception. Therefore, a set of linguistic terms,  $A_i$ , is designated to each  $v_i$ , in order to qualify it, and  $B$  is a set of linguistic terms that qualify  $v$ . Decision rules are defined as a function as follows:  $f : A_1 \times \dots \times A_i \times \dots \times A_n \rightarrow B$ , where  $A_1 \times \dots \times A_i \times \dots \times A_n$  is the Cartesian product of  $A_i$ , means the set of combination of  $(a_1, \dots, a_i, \dots, a_n)$  such that  $a_i \in A_i$ . For example, the value of a compound variable such as Collective factors in figure 3 depends on the values of its two entering variables  $v_1$  and  $v_2$ . Suppose  $A_1 = A_2 = B = \{bad, average, good\}$ , a decision rule could be as follows:  $(bad, average) = average$ . From these combinations the inference rules can be extracted to integrate in the FIS. For each input such as  $(v_1, \dots, v_i, \dots, v_n)$ , several rules could be activated with different degrees. The aggregation of these rules gives a result for the output variable.

### 3.6 Decision as an especial variable

The decision, the root of the tree in figure 3, is considered as a compound variable and it is calculated in the same way. But, it has two main differences with other variables: 1) it is the root of the tree and by definition it is not the entering variable of another variable, 2) directly or indirectly, the arcs are all directed towards

this variable. It means all precedent steps finalize to calculate this variable and it is the output of the system whose modalities depend on the objectives of the studied phase. For example, in a pharmaceutical R&D project the output of a milestone decision can be No Go, Stand by, Go, or Acceleration.

The level of a variable is defined by its distance (number of arcs) between the variable and the root of the tree. At the highest level ( $l_{max}$ ), all variables are elementary and are the inputs of the system (if not, it cannot be the highest, because the tree is a connected graph). At an inferior level of  $l_{max}$ , there is one compound variable (if not, all variables are elementary and there is no need to calculate). Each compound variable including the root, is calculated as explained in precedent section. It should be noted that the uncertainty of the variables, defined in section 3.3, propagate from superior levels into inferior levels and arrives to the root of the tree, wherein it translates to the confidence index of the decision. For a phase of the project, the confidence index of the decision (the variable of the root), is defined by this ratio of all white in-degree nodes of the tree/ total nodes of the tree-1 (excluding the root).

## 4 A FDSS TO ASSESS AVALANCHE RISK

Based on the meteorological, nivological, and topographical available information, a guide plans an itinerary, avoiding avalanches. Information becomes more complete and accurate in time when he advances in his project. Therefore, the main characteristics of our problem are gathered in this example: a series of decisions based on uncertain and dynamic information that becomes more precise step by step. The output of the decision output in a ski resort project is as follows: No Go, Change itinerary, Go. Many methods exist to avoid avalanches (McCammon and Haegeli 2005). We are interested in  $3 \times 3$  formula of Munter (Munter 2006), that is a strategy for Go/No Go decisions to help a guide decide whether to change his itinerary to avoid avalanches, developed by Werner Munter, a Swiss mountain guide. As far as we know, Munter's method is the first method that takes human factors into consideration. According to Munter's method, the guide has to process three categories of uncertain information: human factors, terrain, and snow pack/weather, and has to make sequential decisions at three different times: at home, in the mountain, and at the beginning of a slope. Munter provides a 9-element grid, 3 categories of information by 3 times, wherein a series of variables of each cat-

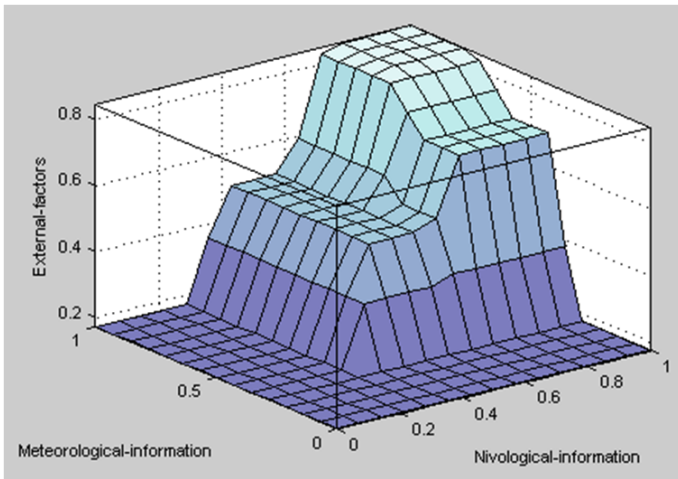


Figure 5: The surface of the *External factors* variable as a function of *Nivological information* and *Meteorological information*

egory has to be collected and evaluated by the guide each time. This evaluation is updated with the new information. Based on Munter's  $3 \times 3$  formula, we propose a FDSS to help the guide, including human factors of the members of his group, decide more effectively and quickly. The proposed FDSS is designed to accept non-precise values for variables and to support the gradual increasing of precision, when new information is received. Moreover, integrating certain human factors such as the experience level, psychological and physical states, helps the guide make a more appropriate decision.

#### 4.1 Organization of variables

The list of variables that has to be taken into account by a guide to avoid avalanches, in the majority comes from Munter's grid and is completed by some variables of the other methods such as Stop-or-Go card of Larcher (McCammon and Haegeli 2005). Munter classified these variables in three categories: human factors, terrain, and snow pack/weather. Respecting this classification, we propose to organize the variables in sub-classes as detailed in figure 4.

#### 4.2 Characteristics of variables

A set of characteristics is given to each variable, in order to study its behavior, its changes, and its impact on the decision. For example, the variables Skill level, as a qualitative variable, and Incline of the slope, as a quantitative variable, are presented here. For Skill level the set of proper-ties is as follows. Type: qualitative, unite: none, range: 3 levels (bad, average, good), state: static (skill level of a skier does not change during one resort), source of information: members of group, measurement methods: discussion, observation (if the guide does not know the members of the group, he asks them at regional milestone, and observes them at local and zonal milestones), and characteristic of information value: incomplete (with hypothesis that the guide does not know the Skill level

of all members of the group).

For Incline of the slope, the set of properties is as follows: Type: quantitative, unite: degree, range:  $0^\circ$ - $29^\circ$ : moderately steep,  $30^\circ$ - $34^\circ$ : steep,  $35^\circ$ - $39^\circ$ : very steep,  $\geq 40^\circ$ : extremely steep, state: static (the slope angle does not change), source of information: maps, photos, Internet, measurement methods: observation, inclinometer, experimentation, descriptive method described by Munter (Munter 2006), and imperfection of information value: imprecise (estimation of a slope angle on a map or evaluation by the guide could be imprecise). Table 1 recapitulates these characteristics.

#### 4.3 Behavior of variables

The guide chooses an itinerary at the regional milestone that could be modified at the local or zonal milestones, if new information invalidate initial hypothesis. Some variables could be missed at regional or local milestones. For example, the variable Discipline of the group is absent at the regional milestone, if the guide does not know the group. Some variables could become precise at local or zonal milestones. For example, for the variable Nivological information, a general evaluation (estimation) is available at the regional milestone. At the local milestone, more information is available about the two entering variables of Nivological information: Snow cohesion and Avalanche, but Warning signs, one of the two entering variables of Avalanche is perceptible only at the zonal milestone. Nivological information is an elementary variable at the regional milestone and becomes a compound variable at the local and zonal milestones, when its two grey entering variables become available.

#### 4.4 Representation of variables

The quantitative elementary variables are the inputs of the system and could be measured by instruments such as thermometer, anemometer, wind sensor, hygrometer, inclinometer, and rain gauge. The qualitative elementary variables are qualified by the guide. The compound variables are determined by their entering variables. For example, the variable *External factors* that is composed of Nivological information and Meteorological information, is determined by its two entering variables :  $External\ factors = f(Nivological, Meteorological)$ . The two variables Nivological information and Meteorological information have three modalities: bad, average, good. the variable External factors has four modalities: bad, average, satisfactory, and good. Suppose that the value of the variable Nivological information  $\in [0, 10]$ . Using classic sets, for a given value of Nivological information, we only have two possibilities: 0 or 1 (bad or good). Using fuzzy sets, we could give a number in  $[0, 1]$  to evaluate this variable. Membership functions

allow to represent the subsets bad, average, and good that divided  $\in [0, 10]$ . To model these linguistic terms, we propose trapezoidal membership functions that are widely applied in fuzzy decision-making, based on experts' opinions (Simon et al. 2007) and correspond to our need. Since, the gap between classic sets and human mental representation is due to strict borders of classic sets. For extreme cases classical sets are appropriated. For the value of Nivological information, the interval  $[0, 3]$  is completely bad (extreme case), there is no need to differentiate 1 or 2. A trapezoidal membership function allows to have an interval such as  $[0, 3]$ , as the kernel of the subset that represents the term bad. Therefore trapezoidal membership functions, as a compromise between classic and fuzzy sets, are suitable to represent extreme cases such as classical sets and to solve the problem of strict borders by fuzzy sets.

#### 4.5 Inference rules

To calculate the value of each compound variable from its entering variables, a set of inference rules is requested. To create these inference rules, we study the impact of entering variables. For example, the two entering variables of External factors have to be compared. As we can see in figure 4, Nivological information is composed of Snow cohesion and Avalanche information,  $Nivological = f(Cohesion, Avalanche)$ . The Meteorological information is composed of Temperature, Wind, and Visibility,  $Meteo = f(Temperature, Wind, Visibility)$ . Their impact on External factors are not the same. According to the opinion of our expert<sup>1</sup> the variables Cohesion of snow and Avalanche information are very important criteria that should be taken into consideration to avoid the risk of being caught in avalanche. Thus, Nivological information is more decisive than Meteorological information. Inference rules are easier to create for the extreme values than intermediate values. Adopting a cautious approach towards risk, if one of Nivological information and Meteorological information is bad, the variable the External factors is also bad. the variable External factors is good, if both Nivological information and Meteorological information are good. Hence, Nivological information is more important than Meteorological information, one of the inference rules can be as follows. If Nivological information is average and Meteorological information is not bad, the External factor is average. If Meteorological information is average and Nivological information is good, the External factor is satisfactory.

The result of these rules is illustrated in figure 5. The value of External factors comparatively changes between 0 and 1 and increases more with the increase of the value of Nivological information than the one of the value of Meteorological information.

<sup>1</sup>The authors express thanks to François Gil, guide of Albi French Alpine Club for sharing his opinions and experiences.

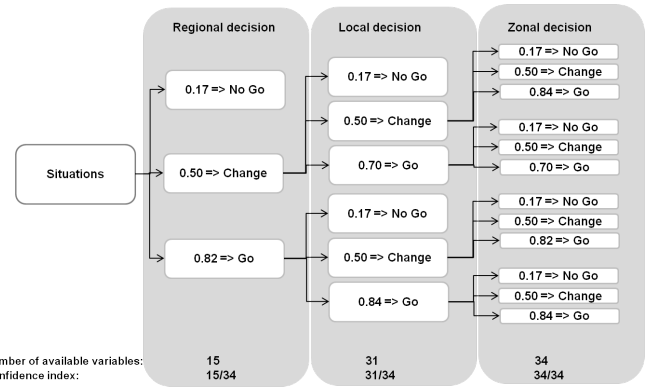


Figure 6: Simulation results

## 5 RESULTS AND DISCUSSION

To choose an itinerary, a guide makes decisions at three milestones: at home (regional decision), in the mountain (local decision), and at the beginning of a slope (zonal decision). To help the guide to make decisions more quickly and effectively, the proposed FDSS calculates the value of the decisions at each milestone. The Go/No Go decision, the root of the tree in figure 4, depends on 34 variables. At the regional milestone, only 15 variables are available. At the local milestone, the value of 16 other variables are known. At the zonal milestone, all the variables are known with precision. Each time a decision is required, 3 simulations are achieved, at the first time (regional milestone): a pessimist one (situation 1), a middle one (situation 2) and an optimistic one (situation 3) that determine the given values of leaf variables to calculate the decision value. When the decision is No Go, the simulations are stopped since the guide would decide to stop the tour. As it is shown in figure 6, the proposed FDSS includes 15 scenario. The results of the FDSS are compared with the results of a naive decisional approach that, as human behaviors when a great deal of information has to be processed, would take into account only the variables that could look more important such as the meteorological information and the depth of the new snowfall. An analogy with two series of accident is made in order to conduct the decision in the simulations: (1) three recent avalanches occurred in the weekend of 18-20 March 2011, in Haute-Savoie, a French department<sup>2</sup>, (2) one week later, on 26 March 2001, in Bourg-Saint-Pierre, in the canton of Valais in Switzerland, another avalanche caused at least four deaths<sup>3</sup>. Several crucial variables are ignored by the skiers. The analogy with the accident cases shows that the guide would be optimistic with the known variables at the regional milestone. The FDSS would calculated 0.82 and therefore to continue the tour, with a confidence index of  $\frac{15}{34}$ . At the local milestone, the analogy

<sup>2</sup><http://alpes.france3.fr/info/alpes--8-morts-en-un-week-end-67951452.html>

<sup>3</sup>News on French public television channels of 27 march 2011, available on <http://www.2424actu.fr/actualite-du-jour/>



with the accident cases shows that the guide would also be optimistic with a confidence index of  $\frac{31}{34}$  and then pursue their ski tour. Finally, at the zonal milestone, different values of all variables are known. For the case (1) the variable Temperature gradient, that has a crucial impact on the variable Cohesion of snow, (see figure 4), and the Danger rating (due to a hilly landscape) are known. For the case (2) the following variables are known: Danger rating (considerable), Group size (there were 11 people), Risky elements (trees, narrow corridor), Cohesion of snow that depends on Temperature (mild), and Incline of the slope (steep). Based on the values of these variables that characterize the situations, the FDSS gives a decision value decreased till 0.17 in the both cases. It means the situations are risky and the guide has not to go. Contrary to that, a naive approach that only takes into consideration some of the available information would ignore this piece of information. By applying this naive approach, the guide would decide to go, as it happened in the both case (1) and (2).

This comparison shows how an approach that does not integrate all information can lead to disastrous situations. A such FDSS is then able to allow process a high number of uncertain variables and alarm signals. Therefore, we think that it could help skiers avoid avalanches.

## 6 CONCLUSIONS AND PERSPECTIVES

In project management, the decision-maker has to cope with uncertainty in a sequence of milestone decisions wherein information become complete little by little. Suspending the decision, waiting for new information, or taking into account only the available information could unfavorably affect the decision. In this approach, we try to reproduce human reasoning process, applying a fuzzy inference system, to support decision under uncertainty. A typology for uncertainty generators is proposed, integrating three main classes: subject, object, and context. The main steps of the proposed approach are as follows. First, the variables that influence decision are identified, collected, and organized according to the classes of the proposed typology of uncertainty generators. Second, a set of characteristics that describes each variable is established. Third, the availability of each variable according to different project's phase is studied. Fourth, the variables are evaluated and ordered according to the importance of their impact on the decision. Fifth, the inference rules are created, taking into account the order of importance of the variables. An application case for a ski resort project illustrated the proposed method. The results are compared with a naive decisional approach to cope with uncertainty and shows the proposed approach is effective. As a perspective, we propose to study the case wherein it is not possible to identify all requested variables at the beginning of the project. To define a more convenient con-

fidence index of the decision, the importance of each absent variable could be taken into account. Another perspective is the application the model to collective decision in industrial cases such as Go/No go milestones in drug development projects that face a high degree of uncertainty.

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