

Fuzz-iDEVS: Towards a fuzzy toolbox for discrete event systems

P.-A. Bisgambiglia
University of Corsica - CNRS
UMR 6134
Qartier Grossetti, bat 018
20250 Corte, FRANCE
bisgambiglia@univ-corse.fr

Pr. P.A. Bisgambiglia
University of Corsica - CNRS
UMR 6134
Qartier Grossetti, bat 018
20250 Corte, FRANCE
bisgambi@univ-corse.fr

E. de Gentili
University of Corsica - CNRS
UMR 6134
Qartier Grossetti, bat 018
20250 Corte, FRANCE
gentili@univ-corse.fr

J.F. Santucci
University of Corsica - CNRS
UMR 6134
Qartier Grossetti, bat 018
20250 Corte, FRANCE
santucci@univ-corse.fr

ABSTRACT

In this paper, we present a set of tools for the simulation of fuzzy systems. The described methods allow to take into account and to handle a lot of imperfect parameters for the studied systems. The methods developed are based on fuzzy logic and DEVS formalism. Their goal is to expand fields of application of simulation environments, and to foster interdisciplinary collaborations. At first, we have applied them to study the spread of forest fires. This application was developed in collaboration with the fire-fighters.

Categories and Subject Descriptors

I.6 [Computing Methodologies]: Simulation and Modeling; I.2.3 [Computing Methodologies]: Artificial Intelligence—*Deduction and Theorem Proving*; I.5.1 [Computing Methodologies]: Pattern Recognition—*Models*

Keywords

Simulation, Fuzzy Toolbox, Discrete Event, Fuzzy System, Fuzzy Logic

1. INTRODUCTION

The study of complex systems and the taking into account of fuzzy data aroused enthusiasm from the scientific community, but also from industrialists, for the approximate modeling methods and especially the 'Fuzzy' theories.

Study of complex natural phenomena led us to use these modeling approaches. Within the framework of the classi-

cal logic, a proposal is either true or false or undetermined. However, in this reasoning, the human being relies on fuzzy information and imperfect data (inaccurate, uncertain, and incomplete). Nevertheless, his reasoning may be coherent and lead to correct results.

The 'Fuzzy' theories are a set of theories of mathematical concepts generally proved and tested, a formal framework for modeling and interpretation of fuzzy proposals (knowledge) and imperfect data. A proposal as "tomorrow there will be a lot of wind" is both inaccurate or uncertain and incomplete (according to Zadeh [15]):

- inaccurate because we can not know how to quantify "a lot of wind"? An inaccuracy is a difficulty in articulating a fact, that is on its content "about 20 km/h"; it does not give an accurate value but an interval. It generally occurs when the data is expressed in a linguistic way as "a lot";
- uncertain, because we do not know how to be sure that tomorrow there will be really much wind, uncertainty is a doubt about the validity of an act. It refers to the veracity of the information. It is a coefficient given to a proposal which can be true or false;
- incomplete, because from this proposal we do not know exactly the true speed of the wind at a given time. Incompleteness is a lack of knowledge, or the partial knowledge on some features of the system. They may be due to the inability to get information or to a problem which occurred during the acquiring of the knowledge. The incompleteness can be seen as a particular case of inaccuracy.

These three types of imperfections are not independent from each other, although they are naturally handled by humans. Trying to transcribe them on a computer can be complicated: computers do not have our understanding abilities.

Our main aim is to build a fuzzy toolbox to take into account, in the same modeling and simulation formalism, this different types of imperfection.

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We chose the DEVS multi formalism [21] because it brings together in a coherent way several modeling method or formalisms, but also because it facilitates the design, simulation and validation of models. The interest of this toolbox is to enable the study of fuzzy systems, i.e. which parameters are inaccurate, or which behavior is uncertain or incomplete (systems described by men or by imprecise measuring instruments). These types of systems are commonly encountered in the study of complex phenomena. Three new DEVS modeling methods are proposed, one for each imperfection.

In the first part, we get back to the mathematical tools to take into account these imperfections. In the second section, we present briefly DEVS formalism. In part three, four and five, we describe three new modeling methods. Before concluding, we present the application of a part of these methods for studying the spread of forest fire.

2. FUZZY LOGIC

Fuzzy logic is an extension of classical logic. It was presented by Zadeh [15] as a framework for the approximate reasoning, a mathematical theory whose purpose of study is fuzzy systems. The approximate reasoning and treatment of inaccurate and uncertain facts are quite natural for human beings. For reasoning about such knowledge, classic modeling is not sufficient, in effect in this case, the approximations on variables generate, at the end, relatively large errors.

Fuzzy modeling, deals with the fuzzy values from the beginning, allowing the final to obtain a range of values (inaccuracy) larger but fairer. According to Zadeh [19] fuzzy modeling provides approximate but effective ways to describe the behavior of systems that are too complex or too badly defined to allow the use of a precise mathematical analysis. The study of these systems requires consideration of inaccuracies, uncertainties but also by a relevant and efficient reasoning on the system as a whole (input and output variables, behavior).

In this section, we present the mathematical basis of fuzzy logic to make this reasoning. Fuzzy sets theory [15] allows to take into account the inaccuracies, theory of possibility [18] deals with the uncertainties, and the study of fuzzy systems can perform approximate reasoning [16] and include inaccuracies, uncertainties and incompleteness.

2.1 Fuzzy Sets Theory

Fuzzy Sets Theory is a mathematical theory in the field of abstract algebra. It was introduced by Zadeh in 1965 [15], we can infer from such a theory a new logic which bypasses the principle of excluded elements, unlike conventional membership notions. Fuzzy logic [20] is based on the concept of fuzzy sets. The definition of a fuzzy set answers to the need for representation of inaccurate or uncertain knowledge or because they are expressed in natural language by an observer who gives little detail or is unreliable, either because they were obtained with observation instruments that produce errors or are unclear.

In a reference set E , a fuzzy set f in E is characterized by a membership function μ_f (fig.1), which associates every element $x \in E$, the degree $\mu_f(x)$ between 0 and 1, where x is in f .

The concept of fuzzy set aims to make gradations in the membership of an element x to a class f , i.e. to allow an element to belong more or less strongly to this class.

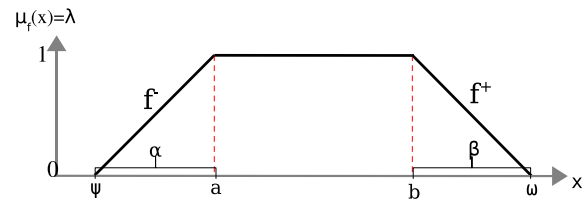


Figure 1: Fuzzy set example

The fuzzy sets theory also provided a whole set of mathematical methods to manipulate the fuzzy sets.

2.2 Theory of possibility

This theory is the second part of fuzzy logic. It is based on the possibilities functions, as the fuzzy sets theory is based on the membership functions. The theory of possibility was introduced in 1978 by Zadeh [18], in conjunction with the fuzzy sets theory, to deduce of inaccuracy knowledge; it introduces a way to take into account the uncertainties on the knowledge.

The possibility function Π associated to each event of a universe Ω a value between 0 and 1 which defines the possibility degree of the event: $\Pi : u \in \Omega \rightarrow \Pi(u) \in [0; 1]$.

2.3 Approximate reasoning

Fuzzy systems use a knowledge representation using fuzzy rules, a way to explain normal decision processes. They express concepts using linguistic terms, as the human representation, for example, "quick wind" instead of "wind stronger than 40km/h". There is a correlation between linguistic variables and associated values.

A linguistic variable [17] is a variable which take its values in a set of symbolic "words"; defining the categories of a reference set. For example, a linguistic variable is defined by a symbolic variable V : "wind speed", by a set of reference $X \in \mathbb{R}^+$, and a set of fuzzy sets denotes wind speeds $T_v = [\text{low, moderate, quick, violent}]$.

A fuzzy proposal is defined from a linguistic variable (V, X, T_v) by the characterization "V is A", such as "wind speed is fast".

A linguistic modifier M is an operator which allows any fuzzy characterization A of V , to produce a new characterization that $A \in M(T_v)$. For example, a linguistic modifier can characterize the wind speed as "very violent".

A fuzzy rule is a fuzzy proposal of the form "if p then q" using fuzzy involvement between two proposals p and q. These rules can describe the behavior of a fuzzy system with the combination of one or more fuzzy proposals. For example, "if the wind speed is fast and vegetation is dry then fire hazards are important". If inaccuracies and uncertainties are liked, it is possible to use the possibilities theory on a fuzzy set. But if the behavior of the system is not precisely known (incomplete) tools such as the approximate reasoning and fuzzy inference systems permit to describe the behavior of the system and exploit the results.

The fuzzy inference systems (FIS) are composed of a collection of fuzzy rules which describe as a textual form (linguistic) system behavior. The design of FIS is generally based on expertise knowledge for the definition of linguistic term of each variable (set of membership functions), and on learning algorithms for the generation of rules. FIS is to be used when: (1) there is a human expertise that we

want to exploit and introduce in automatic systems, (2) we want to extract knowledge from digital data, by expressing it in a language close to the natural language, (3) to create a man/machine interface, give explanations or immediately interpretable diagnostics.

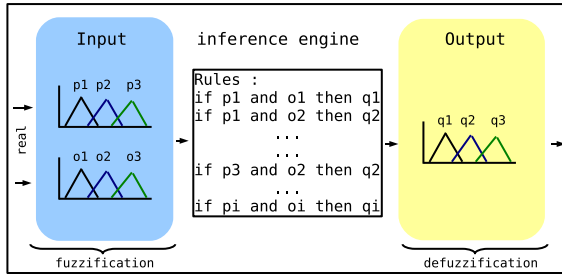


Figure 2: FIS example

Achieving an fuzzy inference system goes through several steps (Fig. 2), the fuzzification and defuzzification variable input / output and the achievement of an inference engine. Fuzzification is the operation which transforms a real value into a fuzzy value, and the reverse operation is called defuzzification [2]. The fuzzification is the step that quantifies with linguistic or fuzzy values, the crisp values of a variable. A fuzzifier variable is a delicate phase of the process implemented by the fuzzy logic, because you have to know all possible variations of variables. Defuzzification is a decision-making phase that can transform a fuzzy variable in crisp variable.

In this part we presented the various tools of fuzzy logic to the inclusion of imprecision, uncertainty and incompleteness. Since the 70s many work permit to establish a solid mathematical basis for the representation and manipulation of data set from these theories. Their integration in a modeling and simulation framework can be very interesting because it would allow studying a lot of imperfect systems.

3. DEVS

Modeling can be defined as an operation by which the model of a phenomenon is established and put into equation in order to obtain a simplified, interpretable and simulable representation of it. Since the seventies, formal work has been conducted to develop the theoretical foundations of modeling and the simulation of dynamic discrete event systems. DEVS (Discrete Event system Specification) [22] was introduced as an abstract formalism for the modeling of discrete events. It allows the modeler to totally isolate himself from the implementation of simulators and is based on a simulation which is driven by events (not by the time).

3.1 Principle of DEVS modeling

DEVS formalism can be defined as a universal and general methodology which provides tools to model and simulate systems, the behavior of which is based on events. It is based on the systems theory, the notion of components and enables the specification of complex discrete event systems in modular and hierarchical form. The DEVS formalism is based on the definition of two types of model: atomic models and coupled models.

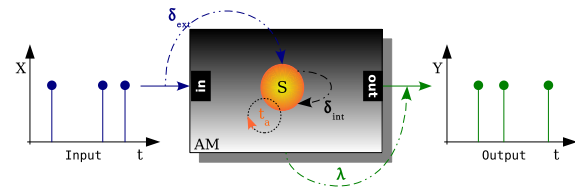


Figure 3: Behavior of an atomic model

3.1.1 Atomic model

The atomic model (fig.3) provides an autonomous description of the behavior of the system, defined by states, input/output functions and internal transitions of the component. It is characterized by the following formula:

$$AM : < X, Y, S, t_a, \delta_{int}, \delta_{ext}, \lambda > \quad (1)$$

With:

- X : all the input ports;
- Y : all the output ports;
- S : all the system states;
- t_a : the function of bringing forward the time (or the lifespan of the state);
- δ_{int} : the internal transition function. It enables the passing from a state S_1 at instant t_1 , to a state S_2 at instant t_2 when no other external event occurs during the lifetime of the state $t_a(S_1)$;
- δ_{ext} : the external transition function. This specifies how the atomic component changes (transition from the state S_1 to the state S_2) when an input occurs (external element) before $t_a(S_1)$ has run out;
- λ : the output function.

3.1.2 Coupled model

The coupled model is a composition of atomic models and/or coupled models. It is modular and presents a hierarchical structure which enables the creation of complex models from basic models. It is described in the form of :

$$CM : < X_M, Y_M, C_M, EIC, EOC, IC, L > \quad (2)$$

With:

- X_M : all the input ports;
- Y_M : all the output ports;
- C_M : the list of models forming the C_M coupled model;
- EIC : all the input links connecting the coupled model to its components;
- EOC : all the output links connecting the components to the coupled model;
- IC : all the internal links connecting the components between themselves;
- L : the list of the priorities between components.

In DEVS, each model is independent and can be considered as its own entity or as a model of a larger system. It was shown in [21, 13] that DEVS formalism is closed under coupling, that is to say that for each atomic or coupled DEVS model it is possible to build an equivalent DEVS atomic model.

3.2 Principle of simulation

Performing a simulation requires the precise definition of behavior as well as the description of interactions existing between the entities of the model. One of the important properties of DEVS formalism is that it automatically provides a simulator for each one of the models. DEVS establishes a distinction between the modeling and the simulation of a model in such a way as any DEVS model can be simulated without it being necessary to implement a specific simulator. Each atomic model is associated to a simulator in charge of the temporal synchronization of the underlying components. The totality of these models is managed by a specific coordinator called Root [21]. Each model communicates thanks to the sending and the reception of several types of messages. The principle is described in [21, 13]. Each message generates events which are stocked in a time-plan schedule, which is a structure of data composed of events classified in chronological order, the head of the schedule representing the immediate future and the tail the more distant future. The simulation consists in making time evolve and provoking the changes of state predicted by the events.

Numerous frameworks exist which integrate the DEVS formalism, but when it is replaced in the specific context of a domain of application; The DEVS formalism must be adapted and extended. Indeed, the DEVS methodology can not model all types of system. In the next section we present three new approximate modeling methods, they are or will be integrated into the pythonDEVS¹ framework to study fuzzy systems.

4. IDEVS

In the following papers [4, 1, 3] we present a new DEVS method that allows to study inaccurate systems. This new approach called iDEVS, for inaccurate discrete event systems specification, was developed to be complementary with the Fuzzy-DEVS [11] and Min-Max-DEVS [7] formalisms. From the study of these two methods we defined objectives and constraints to respect. Fuzzy-DEVS treats uncertainty for the changes of states of models and Min-Max-DEVS treats fuzzy delays between digital circuits.

4.1 Objectives and Issues

iDEVS method can treat the inaccurate quantities represented in the fuzzy intervals form, according to the fuzzy sets theory. It is an extension of DEVS formalism, it respects all its constraints. For example, a iDEVS model whose all parameters are defined as accurate has the same behavior as a DEVS classic model.

To allow the taking into account of inaccuracies in all settings DEVS models without having to modify the simulation algorithms, as is the case in Fuzzy-DEVS and Min-Max-DEVS, we have defined new types of models. In fact, in the DEVS formalism, an inaccuracy of time on the lifespan of

¹<http://moncs.cs.mcgill.ca/MSDL/research/projects/DEVS/>

a state causes the simulation. If we do not know precisely the lifespan of the state we can not continue the simulation. To answer this problematic in the modeling part, we have added to the time advance function (\tilde{t}_a algo. 1) a specific function that treats these cases.

Unlike formalisms Min-Max-DEVS and Fuzzy-DEVS with this method, simulation algorithms do not have to be changed, so the iDEVS method can be imported into any DEVS framework, without having to reprogram whatever be, just using the data structure defined. The coupling between the DEVS formalism and the data structure used to simulate systems with inaccurate parameters.

4.2 Description

iDEVS is based on the fuzzy sets theory for representation and manipulation of fuzzy quantities, a fuzzy quantities is an inaccurate interval or number. Thanks to the fuzzy arithmetic, an extension of mathematical operators to fuzzy quantities, we can model and handle DEVS systems with inaccurate parameters.

To make a link between DEVS formalism and the fuzzy sets theory, we created a library (object class called Fuzzy-Interval) to build object representing inaccurate variables. This library was then incorporated into the DEVS formalism. It includes a set of all functions from the extension principle or fuzzy arithmetic for handling fuzzy quantities. The chosen data structure is an interval, or a fuzzy number, and may be defined by four points $[a, b, \psi, \omega]$ or two profiles $[f^-, f^+]$ (fig.1). A profile represents the left or right part of the membership function of the interval.

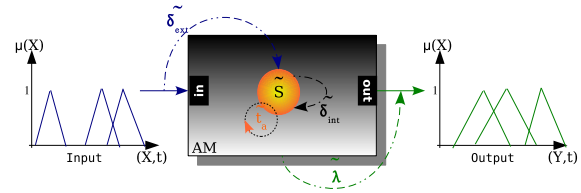


Figure 4: iDEVS atomic model

Considering the DEVS formalism, we have identified several inaccurate factors, as the values and times of events (DEVS event: $(port, time, value)$, iDEVS event: $(port, \tilde{time}, \tilde{value})$). To take into account all the inaccuracies models without having to modify the simulation algorithms, we have defined new atomic and coupled models. We designed so that their changes are imperceptible to the final user, unless it wants to program those models. The atomic model iDEVS presented included all our changes to meet our problem. Its use permits to model systems with inaccurate parameters. It is possible to use it (include) in any existing DEVS framework. All information concerning are detailed below and figure 4:

$$AM_{iDEVS} := \langle \tilde{X}, \tilde{Y}, \tilde{S}, \tilde{t}_a, \tilde{\delta}_{int}, \tilde{\delta}_{ext}, \tilde{\lambda} \rangle \quad (3)$$

With:

- $\tilde{X} = \{(p, \tilde{v}) \mid p \in \text{input ports}, \tilde{v} \in \tilde{X}_p\}$: the list of input ports, each port is characterized by a couple (port number/value), where the value can be defined as accurate or inaccurate;

- $\tilde{Y} = \{(p, \tilde{v}) \mid p \in \text{output port}, \tilde{v} \in Y_p\}$: the list of output ports, each port is characterized by a couple (port number/value), where the value is accurate or inaccurate depending on the behavior of the model;
- \tilde{S} : all state or state variables accurate S or inaccurate \tilde{S} system $S \in \tilde{S}$;
- $\tilde{t}_a(\tilde{S}) \rightarrow R^+$: time advance function, algorithm 1 show this function \tilde{t}_a ;

Algorithm 1 time advance function \tilde{t}_a

```

// declaration of class variables
FuzzyInterval  $\tau = [0, 0, 0, 0]$  // interval representing the time
to end simulation
real  $\Lambda$  // the sum of membership degrees  $\lambda$  defuzzification
real  $\text{nbrDefuz} \leftarrow 1$  // variable that counts the number of
defuzzification
real  $\text{moy}\Lambda = \frac{\Lambda}{\text{nbrDefuz}}$  // variable that keeps the average  $\lambda$ ,
 $t$  is returned at the end of each simulation model
// time advance function
function real  $\tilde{t}_a(\text{state } \tilde{S})\{$ 
   $\sigma$  the lifespan of the state  $\tilde{S}$ 
  if  $\sigma$  is accurate //  $\sigma$  is tested, if  $\sigma$  is accurate the function
 $t_a$  has a classic behavior
     $t_a \leftarrow \sigma$ 
     $\tau \leftarrow \tau + \sigma$  // interval  $\tau$  increases in  $\sigma$ , end simulation
will provide a interval time
  else
     $t_a \leftarrow \sigma.\text{coefEEM}()$  //  $\sigma$  is a instance of the
class FuzzyInterval we apply the defuzzification method
 $\text{coefEEM}()[2]$ 
     $\Lambda \leftarrow \Lambda + \mu(\sigma.\text{coefEEM}())$  //  $\Lambda$  is the sum of defuzzifi-
cation  $\lambda$ , function  $\mu(x)$  return the value  $\lambda$  for  $x$ 
     $\text{nbrDefuz} \leftarrow \text{nbrDefuz} + 1$ 
     $\tau \leftarrow \tau + \sigma$  // we add to the interval  $\tau$  to the interval  $\sigma$ 
  return  $t_a$ 
}

```

- $\tilde{\delta}_{ext} : \tilde{Q} \times \tilde{X} \rightarrow \tilde{S}$: external transition function, where :
 - $\tilde{Q} = \{(\tilde{S}_i, e) \mid \tilde{S}_i \in \tilde{S}, 0 \leq e \leq t_a(\tilde{S}_i)\}$: the set of the accurate or inaccurate states $\tilde{S}_{\{1,2,\dots,n\}}$;
 - \tilde{e} : is the fuzzy time elapsed since the last transition, the role of external transition specifies how the atomic model changes its state (from \tilde{S}_1 to \tilde{S}_2 when a accurate or inaccurate input occurs (external event) before $t_a(\tilde{S}_1)$ has expired;
- $\tilde{\delta}_{int} : \tilde{S} \rightarrow \tilde{S}$: internal transition function. It allows to switch between a state \tilde{S}_2 to the date t_1 , to a state \tilde{S}_1 at the moment t_2 when external event happens during the lifespan of the state $t_a(\tilde{S}_2)$;
- $\tilde{\lambda} : \tilde{S} \rightarrow \tilde{Y}$: output function, it returns the model outputs and the class variables τ and $\text{moy}\Lambda$.

The data handled by iDEVS atomic model are represented by a quadruple $[a, b, \psi, \omega]$ (fig.1), defined in the class called FuzzyInterval, a and b represent the vertex of the interval,

ψ and ω bounds left and right. If $a=b$ and $\psi=\omega=0$ iDEVS model becomes a classic DEVS model (not fuzzy) handling accurate data. Equation 3 presents in detail the general iDEVS atomic model. The tilde ($\tilde{\quad}$) on a parameter means that it is inaccurate or that it handles inaccurate variables. The input values may be inaccurate \tilde{X} ; upon receiving a input value, fuzzy external transition function ($\tilde{\delta}_{ext}$) is triggered, it updates the state \tilde{S} and its lifespan t_a according to the specifications defined by the designer. If no entry is found before the end of lifespan, fuzzy internal transition function and output function are triggered. $\tilde{\delta}_{int}$ updates the state of the system according to specifications set by the designer and $\tilde{\lambda}$ generates simulation results \tilde{Y} .

For the transition from DEVS models to iDEVS models, behavioral functions (δ_{int} , δ_{ext}) of DEVS classical model have not been changed. If the data are inaccurate, they will manipulate objects of FuzzyInterval type. Their structure and behavior are the same. The functions (\tilde{t}_a and $\tilde{\lambda}$) have been changed. The output function returns more information but has the same behavior. The \tilde{t}_a function tests if the lifespan of the state is accurate or inaccurate. In the second case a defuzzification function is used to transform the inaccurate data in crisp data (algo. 1). We have added this algorithm to avoid inaccurate simulation times. An inaccuracy about simulation time leads to structural changes at the level of simulation algorithms and is incompatible with the classical DEVS formalism.

The iDEVS coupled model is a DEVS coupled model which allows to couple DEVS or iDEVS atomic or coupled models. To use the iDEVS method, in any DEVS framework, you have just to import the FuzzyInterval class and add algorithm 1 in the time advance function code, or to use the iDEVS atomic model that we presented.

This new approach does not take into account inaccuracy, uncertainty and incompleteness. Only inaccurate parameters are processed. After this first stage we are currently working on the consideration of uncertainty and incompleteness. For that we believe offer improved Fuzzy-DEVS formalism. Fuzzy-DEVS can already take into account the uncertainties related to the behavior of a system, but its simulation algorithms are not very efficient. Moreover, the uncertainties are taken into account on the transition functions between states. We are also working on the integration into DEVS of a fuzzy inference model to study systems inaccurate parameters. In both of the following parts these approaches are presented, although we are still in the study phase.

5. UDEVS

A natural or artificial system is generally described as a set of characterized proposals. Some of these proposals may be imperfect, i.e. inaccurate (value), or uncertain (occurrence). The aim of the uDEVS method (uncertain DEVS) is the definition of a simulator DEVS which manages uncertain events. Just as the Fuzzy-DEVS formalism [11] which deals with uncertainties linked to the change of state.

The uDEVS method generalizes Fuzzy-DEVS approach; it works at a higher level to take into account the uncertainties directly at events, i.e. at the schedule simulation. This evolution brings several important changes in classical DEVS formalism: (1) the addition of an achievement degree (II) to the events, an uDEVS event is characterized by the formula ($\text{port}, \text{time}, \text{value}, \text{II}$), and, as in Fuzzy-DEVS, the

DEVS simulation algorithms must be changed. (2) in the simulation part, it is necessary to add a second schedule that sorts the events according to time and their achievement degree; then, we must rethink the simulation algorithm which purpose is to chose which event will be triggered:

- If its achievement degree is higher than a coefficient determined by the user (e.g. 0.7) event is considered highly achievable, and is therefore treated as a classical DEVS event.
- If its achievement degree is lower than the coefficient should be applied a method of consideration, based on a formula Sup Min, as shown below:

Sup (Min (set of achievement degree of current events (t), set of achievement degree of the next events (t +1), set of achievement degree of generated events (tn)))

$$Sup(Min(\prod_{E \in event} E_t, E_{t+1}, E_{t_n})) \quad (4)$$

We choose the next event E_{t+1} as one with the highest achievement degree among current events E_t and events potentially generated by selected event E_{t_n} . The next event is an event that is already in the schedule, generated event is an event that can be created following the execution of the current event. It has not yet been placed in the schedule.

The last step of our reasoning is about the initialization achievement degree of events. They can be set side by modeling the designer of the model. In this case, as in Fuzzy-DEVS, they are attached to the functions of the model (transitions δ or output functions λ). We must also take into account the 'self-generated' events i.e. that generates new events outside the model behavior. In this case we believe set the achievement degree in relation to the degree of the parent event, the number of events generated (son) and a formula that remains to be defined and tested. It is necessary to treat them differently from events far removed in time, and a set of very close events. Indeed, the more the events are close in time the more the impact of their achievement is important.

This new method is still in development phase, we base ourselves on theory of possibilities [18, 6] and the formalisms Min-Max-DEVS [7] and Fuzzy-DEVS [11] to propose new simulation algorithms, taking into account our proposals. uDEVS method have to easily applied in many fields, and can be presented as an improved Fuzzy-DEVS formalism. It must also respect the prerogatives of classical DEVS formalism, including the property of closure under coupling. We want to implement it to spread of forest fires, to take into account the uncertainties resulting from climate variations or changes of vegetation zones (transition the fire from a prairie to a forest). This extension may be used to study systems whose state transitions are not certain (normal state -> burned state, wet vegetation -> dry vegetation). This with be possible thanks to the addition of a coefficient of validity on transition functions.

6. DEVFIS

The fuzzy inference systems are used for reasoning, especially for the simulation of physical or biological systems. They operate from fuzzy reasoning rules, which have the

advantage of managing the progressive phenomena. The design of fuzzy inferences based on expert knowledge for the definition of linguistic terms for each input and output variables, and on learning algorithms to generate rules.

Work has already been done in Greece to determine from a fuzzy inference risk areas in terms of fire [10, 9]. The same study could be conducted in Corsica in collaboration with the SDIS (Service Départementale d'Incendie et de Secours: Departmental/Country Fire Rescue Service). We could define certain risk criteria (weather, population, history, vegetation, etc., risk coefficient) and modeling to determine a risk mapping.

In terms of preventing this approach could be interesting, knowing that we must detect as soon as possible the start of the fire, in order to limit risk and the area burned. The placement of watchmen and rapid intervention units could be optimized and updated regularly depending on weather conditions. To describe this system and coupled with other meteorological models or land and vegetation models (GIS), we propose to define a new modeling method based on DEVS, iDEVS and uDEVS, which aims to allow specification DEVS inference models. The general problem is to consider the best way to put an inference system in DEVS models, to choose the best inference algorithms to use, and implement a user interface. The interface allows the user to define the system and enter the rules. To do this, a new class FuzzySets has been defined; it contains a set of objects of FuzzyInterval type, defined for the iDEVS approach, and different methods for handling as fuzzy sets. Starting of this class we can represent the inputs and outputs of the system, and the results obtained following the application of fuzzy operators or inferences methods. We propose accordance with the structure of a fuzzy inference system (fig.2), to define a model DEVFIS (Discrete Event Fuzzy Inference system Specification) for each stage of the process of inference, namely:

- one or more atomic models based on a fuzzification method to represent the input of the system;
- one or more atomic models based on a defuzzification method to represent the output of the system;
- coupled model describing the inference engine, which includes a atomic model representing all the rules describing the system, atomic model describing the fuzzy operators employees, and an atomic model representing the inference method (fig.5).

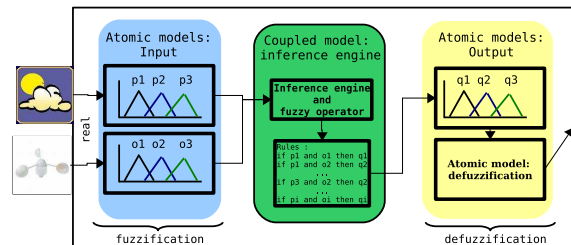


Figure 5: DEVFIS model

The definition of these different models, and the selection and testing of methods of fuzzification, of inferences, and

of defuzzification, are at a preliminary stage. But this new modeling method seems to be very appropriate for the specification of any fuzzy system. It is expected to expand the scope of DEVS formalism to a large number of new fields. This new method of modeling will allow to model to DEVS format the fuzzy inference systems. In the following part, we present an application of the iDEVs method. Ultimately, once uDEVs and DEVFIS will be validated, the three methods will be used to exploit the application. For example, the FIS used to identify some parameters of our models will be directly imported from DEVFIS models.

7. APPLICATION

These last few years have reminded us with force that the fight to combat forest fires has not been won yet. Several methods for the study of the propagation of forest fires exist. Some are used to describe in a more or less in-depth manner, with the help of physical and mathematical equations [12, 14, 8], all the implemented mechanisms. Others closer to a more in the field level of reasoning consider that a large number of parameters may not be taken into account [5, 9].

We have focused our work on two aspects: the fight against fire and prevention; in these two domains, we wish to contribute towards the creation of tools to help the decision making. In face of the extent of the work to conduct, it is necessary to take a gamble on the effectiveness of the action undertaken and on effectiveness with respect to the objectives fixed. This implies permanent adjustments in the strategy of prevention and fire-fighting according to the means available.

In this perspective and in order to conform to the realities in the field, we have undertaken work in collaboration with the SDIS of Northern Corsica. Several courses of action, remaining very close to their needs and concerns, have emerged from this cooperation. The model presented in this part retranscribes in a data processed manner the empirical reasoning of the SDIS firemen undertaken in the field. The information presented in linguistic form has been translated into models with as objective the carrying out of a system in real time.

To implement our methodology, we have followed the following steps: identification of the problem with fire-fighters, identification and modeling of parameters (FIS), definition and programming of models (iDEV and DEVS); simulation; interpretation and exploitation of results. This application is not based on real cases, the data were selected randomly. It aims to validate a theoretical approach. We have begun field work recently. We will soon compare the results of our simulations with real scenarios of forest fires.

7.1 Problem areas

One of the problem areas advanced by the SDIS is the necessity to fastly predict the possible progression of the fire in order to implement an adequate policy to fight it. The latter must take into account their necessities: disposal and use on site of the material and men, methods of intervention. Care is taken first of all of persons, secondly houses and finally vegetation, according to the method called HBE : (in English MBE : man , building, environment). Initially, in order to reply to their concerns, we turned our studies toward the definition of a propagation model in the field. The first stage was the identification of these parameters.

7.2 Identification of the parameters

For a problem as complex as that concerning the study of the forest fire propagation, a large number of parameters must be considered. These parameters are difficult to identify, quantify and model. Moreover, it is easy to see that the majority of them are marked by inaccuracy. Fuzzy logic is therefore a good means of taking them into account.

We have identified three groups of parameters to take into consideration, the vegetation, the topology of the terrain and the weather. These groups can be broken down with for instance: (1) for the weather, the wind: strength, direction and air humidity; (2) for vegetation: type, density, height, humidity, inflammability; (3) for the topology of the terrain: steepness of slope and configuration.

To take into account the influence of the uncertainty and inaccuracy of these parameters, we have defined two models.

The First ones are based on the following assumptions. By hypothesis and following different meetings with the firemen who take between 3% and 8% of the wind speed as basis to approximate the propagation, we consider that in the field, only the wind has a veritable influence on the spreading of the fire. The fire front is schematized by a straight line. To represent its evolution we calculate the coordinates of the intersection point between center of this straight line and a perpendicular segment representing the wind direction. The speed of propagation is considered as constant between two events. The parameters of the vegetation and the terrain are represented by a coefficient initially fixed at 1 and which evolves according to the conditions. If the conditions favor the spreading of the fire, it can be increased. The coefficient is determined from the parameters of the terrain through a fuzzy inference system. Each identified parameter has been modeled, and its influence translated into rules to specify a coefficient of propagation. For this model, we consider the following parameters as fuzzy:

- 3% of wind speed [0.03, 0.03, 0.026, 0.034];
- a coefficient of propagation [1, 1, 0.6, 1.4];
- wind speed [2.7, 2.7, 2.5, 2.9];

The second model describes the evolution of the fire front in terms of zone (vector propagation [5]). The terrain is modeled in terms of its influence on the fire, it is divided into zones, and each zone has its own characteristics. We do not calculate the spread of fire with time, but in terms of changes in zones. On a given zone we consider that the parameters influencing the fire are invariants. The aim of the model is to provide firefighters the ability to predict different scenarios of propagation, and to take into account the structural or behavioral changes on the terrain. The evolution of the model takes place in three stages: (1) it calculates the points of intersection between the fire front and the next affected zones; (2) it assesses the distances travelled by the fire; (3) and it calculates the likely time before the next zone does not is reached. The model is defined on the following parameters:

- coordinates of departure set by use [10;10];
- coordinates delimiting each zone $z_1 : \{[0; 0], [80; 200]\}$, $z_2 : \{[80; 200], [140; 200]\}$, $z_3 : \{[140; 200], [200; 200]\}$;

- coefficient of propagation given by a fuzzy inference system corresponding to the characteristic of each zone (flammability, height and density of vegetation, wind speed on the area, topology field, etc.). The fuzzy inference system was established in collaboration with firefighters $z_1 : \{1.8\}$, $z_2 : \{1\}$, $z_3 : \{1.4\}$;
- wind speed and direction premises
 - $z_1 : \{50 - 70\text{km/h, South West}\}$;
 - $z_2 : \{18 - 22\text{km/h, South West}\}$;
 - $z_3 : \{50\text{km/h, South}\}$;
- percentage of the wind speed that set the speed of fire spread over a zone. It is equal to more or less 3 to 8% of the wind speed, and was defined by firefighters.

7.3 First model

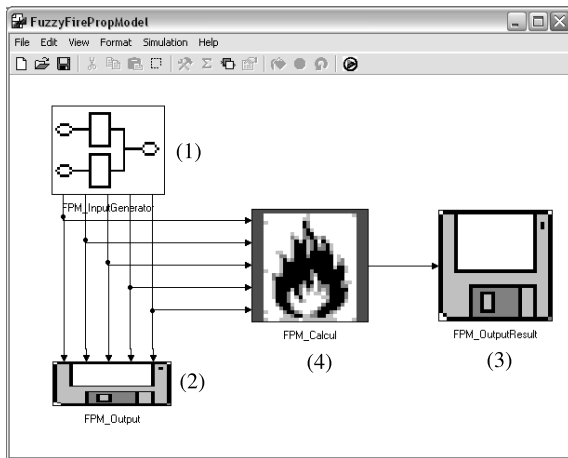


Figure 6: Software structure

This iDEVS model (fig.6) is a coupled model which describes the propagation model. It consists of a coupled model (fig.6 model (1)) to 5 outputs, which generate the parameters of the terrain: coordinates (4,4) of the point representing the fire front, coefficient of propagation, wind strength and direction. Two atomic models enable us to display in a file the output parameters (fig.6 models (2) and (3)), and an atomic model describes the propagation model and calculates the distance covered by the fire (fig.6 model (4)). It takes at input the parameters of the first model. At reception of an input, it updates its state variables by launching the external transition function. This function also puts the lifetime of a state at 0 ($t_a = 0$), which according to the DEVS process, carries out the function of internal transition function. It calculates the new coordinates and launches the output function, which sends the coordinates towards one of the display models. The new coordinates are determined using first order equation type: transport Lagrangian point.

Table (1.a) presents the input data. It is noticed, that the fuzzy data (the vegetation and the power wind) are printed in the form of an interval $[a, a = b, \alpha, \beta]$. The approximate speed of propagation (prC) is a model state value. The table (1.b) shows the results of the simulation of the model. It is

<i>Time</i>	0	
<i>Vegetation</i>	[1, 0.6, 1.4]	
<i>Wind_{powr}</i>	[2.7, 2.5, 2.9]	(a)
<i>Wind_{dir}</i>	10	
<i>X</i>	4	
<i>Y</i>	4	
<i>time</i>	<i>x</i>	<i>y</i>
0	[4, 4, 4, 4]	[4, 4, 4, 4]
1800	[147.5, 78.7, 231.8]	[29.3, 17.1, 44.1]
3600	[291.1, 153.3, 459.6]	[54.6, 30.3, 84.3]
5000	[434.7, 227.9, 687.4]	[79.9, 43.4, 124.5]

Table 1: Input and output data of the first model (with $a = b$)

noted that the outputs of the fuzzy model are fuzzy interval. We can conclude from these results that simulation from an accurate model gives precise but surely erroneous results on the ground scale, the results of table (1), although they are fuzzy, are likely great to fall right or on a scenario which will occur.

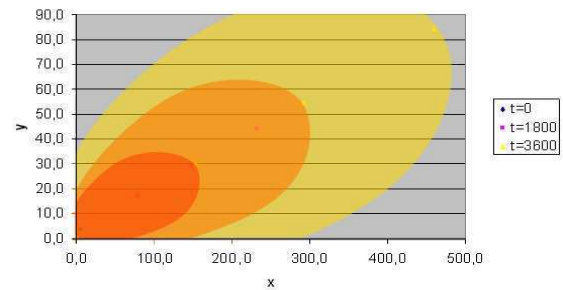


Figure 7: Results sample interpretation

From these results we can deduce several spread scenarios. Figure 7 shows this interpretation. After 3600s, if the parameters are not conducive to the spread, the fire front should be represented by the smallest ellipse. If all the parameters are controlled, the fire should be represented by the ellipse in the center. If the parameters are conducive to the fire spread (dry vegetation, strong wind), the fire front should be represented by the largest ellipse. Based on these data, firefighters can adapt their intervention mode.

7.4 Second model

To represent the system we have identified four DEVS or iDEVS atomic models. The first model (ground model) contains the ground parameters. It returns the start coordinate of the fire and the parameters of the affected zone, and when it receives a message from the propagation model, for each change of zone. The second model (model weather) is a generator that transmits meteorological data, wind speed and direction. The third model (propagation model) is the most important; it calculates the points of intersection between a zone and the fire front. The final model (model display) displays the results of the propagation model.

For this application, the model structure is substantially identical to the one presented figure 6. On the other hand their behavior is totally different, and based on the algorithms described above. The propagation model calculates the time and coordinates of the new zones of impact. The

	X	Y	Distance	Time	Accurate time	membership degree
Zone	80	93.4	108.9	40.3		
	80	80.0	98.9	20.3	17.1	0.7
1	80	68.7	91.3	9.1		
Zone	140	164.9	93.3	172.8		
	140	140	84.8	94.2	75.5	0.6
2	140	119.1	78.3	44.5		
Zone	200	175.5	60.9	48.3		
	200	145.2	60.2	23.9	21.2	0.8
3	200	119.1	60.0	10.7		

Table 2: Simulation result.

returned data are of FuzzyInterval type. The table 2 shows the obtained data. We have, for each zone, coordinates, travelled distance, time before and after defuzzification and the degree of validity of defuzzification times. We can see that the results are relatively good, the membership degree is always greater than 0.5.

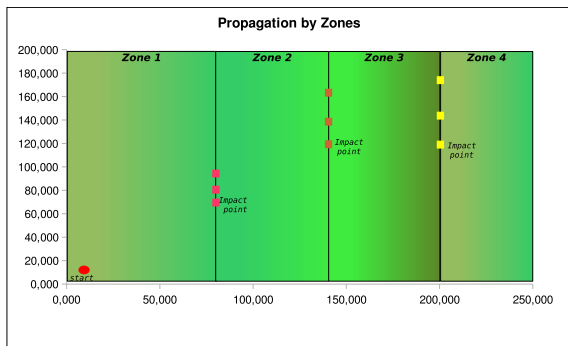


Figure 8: Results sample interpretation

From these data we have recreated the spread of the fire, figure 8. In this figure the four zones are visible, the coordinates of fire start (10.10) and different points of intersection. We can see that more the simulation lasts, the greater the impact interval is high. The angle also plays an important role; it is easy to notice the change in the direction of propagation between the first two zones and the third. From these data simulation, we can conclude that the fire front to reach the four zone in 21 hours with a certainty above 0.6. The fire will have travelled about 244 kilometres in 21 hours. These results may provide firefighters a good database to position their men on the field long before the fire happens. Thus, without fear of endangering men, it is possible to prepare the ground to slow at best the fire front.

The application presented is a theoretical study, it should soon be used on the ground.

8. CONCLUSION AND PERSPECTIVES

This paper presents our work in the fields of modeling and simulation of fuzzy systems. Notably, we have detailed our approach based on the integration of the fuzzy sets theories into multi-modeling DEVS formalism. This method's aim is to help experts in a domain, such as fire-fighters for forest fires, to specify in a simple way the behavior of a complex

Fuzzy Logic			
Inaccuracies		Uncertainties	Incompleteness
Fuzzy sets theory		Possibilities theory	Fuzzy sets and possibilities theories fuzzy inference systems
DEVS			
existing	Min-Max-DEVS + ta function Inaccurate - fuzzy sets theory - simulation algorithm	Fuzzy-DEVS + transition functions uncertain - simulation algorithm	
	our approach	iDEVS	uDEVS DEVFIS
Fuzz-iDEVS			

Figure 9: Summary

system characterized by badly defined parameters.

The basic idea in our methodology is to enable the modeler to specify the fuzzy parameters of models in a simple way.

For now, only iDEVS method has been validated, the two other methods are still in research phase. We believe that these methods can be integrated into a single framework to provide a variety of tools to study systems whose parameters are inaccurate, uncertain or more generally whose behavior is badly defined. Our approach can be used both in the domain of help for decision-making and in crisis management.

The three methods (iDEVS, uDEVS, DEVFIS, fig.9) will be incorporated into a multi-modeling framework. They are complementary, and based on the same principle: to define imperfect data with an appropriate data structure, which also provides a set of manipulation functions. These three extensions of DEVS formalism respect its constraints, it will be possible to couple the models of each, of them in models of higher-level (coupled model). There is not really a tool of its kind, at least as complete. Softwares like Matlab/Simulink² offer fuzzy libraries, but they are restricted to the taking into account of a single category of imperfection.

We must now finalize uDEVS and DEVFIS, and then we will integrate all our methods in the same DEVS framework called Fuzz-iDEVS.

9. REFERENCES

²<http://www.mathworks.com/>

- [1] P.-A. Bisgambiglia, L. Capocchi, E. de Gentili, and P.A. Bisgambiglia. Manipulation of incomplete or fuzzy data for DEVS-based systems. In SCS, editor, *Proceedings of the International Modeling and Simulation Multiconference (IMSM) - Conceptual Modeling Simulation (CMS)*, pages 87–92, 2 2007.
- [2] P.-A. Bisgambiglia, E. de Gentili, P.A. Bisgambiglia, and J.F. Santucci. Discrete events system simulation-based defuzzification method. In *Proceedings of The 14th IEEE Mediterranean Electrotechnical Conference (MELECON)*, pages 132–138, 05 2008.
- [3] P.-A. Bisgambiglia, E. de Gentili, P.A. Bisgambiglia, and J.F. Santucci. Fuzzy simulation for discrete events systems. In *Proceedings of the 2008 IEEE World Congress on Computational Intelligence (WCCI 2008) - IEEE International Conference on Fuzzy Systems (FUZZ-IEEE)*, pages 688–694, 06 2008.
- [4] P.-A. Bisgambiglia, E. de Gentili, J.B. Filippi, and P.A. Bisgambiglia. DEVS-Flou: a discrete events and fuzzy logic-based new method of modelling. *SIMULATION SERIES, VOL 38, PART 4*, pages 83–90, 7 2006.
- [5] P.-A. Bisgambiglia, J.B. Filippi, and E. de Gentili. A fuzzy approach of modeling evolutionary interfaces systems. In IEEE, editor, *Proceedings of the ISEIM 2006, Corte (France)*, pages 98–103, 6 2006.
- [6] P. Bosc, D. Dubois, and H. Prade. An introduction to fuzzy sets and possibility theory based approaches to the treatment of uncertainty and imprecision in database management systems. *2nd Workshop on Uncertainty Management in Information Systems : From needs to solutions*, 1993.
- [7] N. Giambiasi and S. Ghosh. Min-Max-DEVS: A new formalism for the specification of discrete event models with min-max delays. pages 616–621. 13th European Simulation Symposium, 2001.
- [8] A.M. Grishin. *Mathematical modelling of forest fires and new methods of fighting them*. House of the Tomsk State University, 1997.
- [9] L.S. Iliadis. A decision support system applying an integrated fuzzy model for long-term forest fire risk estimation. *ELSEVIER, Environmental Modelling and Software 20 (2005)*, pages 613–621, 2005.
- [10] L.S. Iliadis, A.K. Papastavrou, and D. Lefakis. A computer-system that classifies the prefectures of Greece in forest fire risk zones using fuzzy sets. *ELSEVIER, Forest Policy and Economics 4 (2002)*, pages 43–54, 2001.
- [11] Y. Kwon, H. Park, S. Jung, and T. Kim. Fuzzy-DEVS Formalisme : Concepts, Realization and Application. *Proceedings AIS 1996*, pages 227–234, 1996.
- [12] R. C. Rothermel. A mathematical model for predicting fire spread in wildland fuels. *Research Paper INT- 115*, Ogden, UT: U.S. Department of Agriculture, Forest Service, Intermountain Forest and Range Experiment Station.:40p, 1972.
- [13] H. Vangheluwe. The Discrete Event System specification DEVS Formalism. Technical report, 2001. <http://moncs.cs.mcgill.ca/>.
- [14] R.O. Weber. Modeling fire spread through fuel beds. *Prog. Energy Combust. Sci, vol. 11*, pages 67–82, 1991.
- [15] L.A. Zadeh. Fuzzy sets. *Information Control*, 8:338–353, 1965.
- [16] L.A. Zadeh. The concept of a linguistic variable and its application to approximate reasoning, 1975. parts 1 and 2.
- [17] L.A. Zadeh. The concept of a linguistic variable and its application to approximate reasoning. *Information Sciences*, (9):43–80, 1976.
- [18] L.A. Zadeh. Fuzzy sets as a basics for a theory of possibility. *Fuzzy Sets and Systems*, pages 3–28, 1978.
- [19] L.A. Zadeh. The role of fuzzy logic in the management of uncertainty in expert systems. *Fuzzy Sets and Systems*, pages 199–227, 1983.
- [20] Lofti A. Zadeh. Fuzzy logic. *Computer*, 21(4):83–93, 1988.
- [21] Bernard P. Zeigler, Herbert Praehofer, and Tag Gon Kim. *Theory of Modeling and Simulation, Second Edition*. 2000.
- [22] Bernard P. Zeigler and S. Vahie. DEVS formalism and methodology - unity of conception diversity of application. In SCS Editions, editor, *Proceedings of the 1993 Winter Simulation Conference*, pages 573–579, 1993.