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FUZZY LIFETIME STATE FOR DEVS FORMALISM
Forest Fire Propagation Case

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ABSTRACT: *This paper tries to add a convivial and dynamic structure in DEVS formalism via the time advance function and especially by the state lifetime in the DEVS specification. To do that, we use the fuzzy logic concept to assess each lifetime for each state in order to develop a dynamical structure. This motivated idea is consolidate from the physical systems. Indeed, giving the lifetime of a state is in general roughly done and in the major case this value is just approximated. For some cases, we observe that the dynamic of a system is dependent of its entries, so we can observe a relationship between the input and the lifetime of states. To validate our idea, we simulated wildfire spread by combining fuzzy logic theory and DEVS formalism.*

KEYWORDS: *DEVS Formalism, Time Advance Function, State Lifetime, Fuzzy Logic, Fuzzy Inference System, Wildfire Spread Simulation.*

1 INTRODUCTION

The natural disasters (fires, floods, tsunamis, hurricanes...) have a considerable human and economic cost [Bisgambiglia, 2008]. Their increases these last years reinforce the need to understand and quantify these processes in order to get more control.

Nowadays, the modelling and simulation formalisms are more and more used in order to help, to forecast, and understand these complex phenomena [Papadopoulos, 2011]. Nevertheless, these phenomena are very complex to be studied due to the great number of parameters taken in consideration. In the majority of the cases, these parameters remain uncertain and inaccurate.

The partial knowledge of certain systems implies uncertainty. This point was studied by some theories amongst them, the fuzzy logic which is a well-known theory to represent human being knowledge without an analytical model. Its results are more coherent with respect to objectives and constraints of the system.

In other hand, simulation manages models in order to produce behavioral data, i.e. to evolve/move the states of the model over time [Zeigler, 1984]. Simulation is then similar to experiment [Bertalanffy, 1973], [Fishwick, 1995], given the possibility of predicting the behavior of complex systems.

Our work aims to introduce a concept of fuzzy lifetime into DEVS formalism. This approach is then applied and simulated in forest fires growth.

The present paper stated as follows: At the beginning an introduction is done followed by the second section in which we recall some concepts on DEVS formalism and fuzzy logic.
The third section presents the core of our approach by describing the identified parameters, models and framework related to the present work. The forth section is dedicated to simulations and discussions. At the end, we conclude this work with a conclusion and perspectives.

2 BACKGROUND

2.1 The DEVS Formalism

2.1.1 Introduction

The DEVS formalism "Discrete EVent system Specification", was introduced by Professor B.P. Zeigler [Zeigler, 1976]. It is based on mathematical theory of dynamic systems [Zeigler, 1984]; it is a reference for coupling heterogeneous models. In fact this formalism is adapted to a great number of applications [Zeigler and Vahie, 1993].

Each system is described by two points: functional (behavioral) and structural aspect [Wainer and Mosterman, 2011]. Likewise, DEVS formalism allows two levels of description [Zeigler, 1976], [Zeigler et al., 2000], [Glinsky and Wainer, 2004]. At the lowest level, a basic component called atomic DEVS describes the autonomous behaviour of a discrete-event system. At the highest level; a coupled DEVS describes a system as modular and hierarchical structure.

2.1.2 The Atomic DEVS Model

The atomic models are the basic components of the formalism; they describe the behavior of the system (Figure 1). Their operation is close to the "state-machines". Formally, an atomic model DEVS is specified by 7-tuple (1):

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

Where
X: the set of input events;
S: the set of sequential states;
Y: the set of output events;
δ_{int} : $S \rightarrow S$: internal transition function, models the states changes caused by internal events;
δ_{ext} : $Q \times S \rightarrow S$: external transition function, defines the state changes due to external events;
$Q=\{(s,e) \mid s \in \mathbf{S}.0 \leq e \leq t_a(s)\}$: total states and e describes the elapsed time since the last transition of the current state s;
λ: $S \rightarrow Y$: output function, maps the internal state onto the output set;
t_a: $S \rightarrow \Re_0^+ \cup \infty$: time advance function, represents the lifetime of the state.

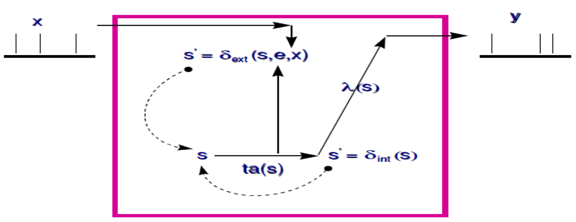

Figure 1: DEVS Atomic model [Zeigler et al., 2000]

2.1.3 The Coupled DEVS Model

A coupled model DEVS is modular and presents a hierarchical structure, which allows the creation of complex models starting from atomic and/or coupled models. It is described by (2):

$$CM=<X_{self},Y_{self},D,\{M_d \mid d \in \mathbf{D}\},EIC,EOC,IC,select>.(2)$$

Where

X_{self} : set of possible inputs of the coupled model;
Y_{self} : set of possible outputs of the coupled model;
D : set of names associated to the model components;
$M_d \mid d \in \mathbf{D}$: set of the coupled model components, these components are either atomic or coupled DEVS model;
EIC: set of External Input Coupling;
EOC: set of External Output Coupling;
IC: defines the Internal Coupling;
Select: $2^D \rightarrow D$: tie-break selector.

2.2 Fuzzy Inference System

2.2.1 The Structure

A fuzzy inference system (FIS) also known as fuzzy logic controller aims to build control law from linguistic and qualitative description of system's behaviour via fuzzy base rules [Zadeh, 1992].

A FIS consists of five basic elements (Figure 2):

- Rule Base expressing knowledge processes introduced by intuition and experimentation with human operators;
- Data Base of the properties of fuzzy sets;
- State interface (Fuzzification): numerical values are represented into linguistic variables with appropriate membership functions;
- Action interface (Defuzzification): transforms the command actions into crisp values useable directly by the process which is modeled;
- Inference engine: makes decisions from activated fuzzy rules, it is the core of the controller.

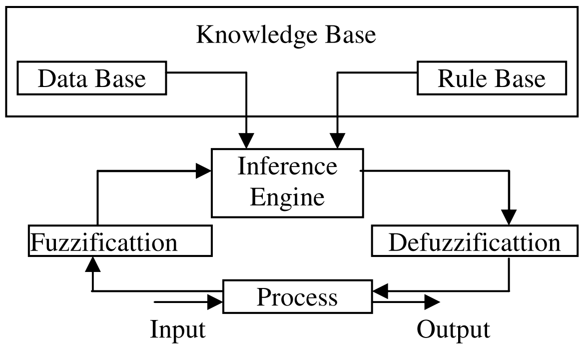

Figure 2: Fuzzy Inference System

2.2.2 Inference

It is the decision-making mechanism; it gives the final conclusion for all activated rules according to the input data.

For an input vector $x=(x_1,\ldots,x_n)^t$ (Figure 3), the fuzzy inference involves the following steps [Glorennec, 1999] :

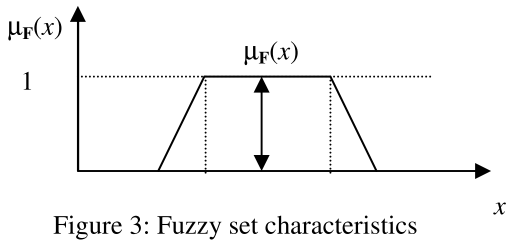

Figure 3: Fuzzy set characteristics

This procedure is applied on the fired fuzzy rules. The general form of each fuzzy rule is given as follows:

R_i :
If x_1 is $\mathbf{X_1^i}$ and .... and x_n is $\mathbf{X_n^i}$ **Then** y is $\mathbf{Y^i}$ (3)

Where $\mathbf{X_j^i}$ is a fuzzy set of the input j and linguistic variable i. i=1 to N and j=1 to n.

1. Calculation of degrees of membership of each input to the different fuzzy sets:

$$\mu_{\mathbf{A_j^i}}(x_j)\,. \tag{4}$$

2. Calculating the truth value of each rule:

$$\alpha_i(x) = \min_j\left(\mu_{\mathbf{A_j^i}}(x_j)\right). \tag{5}$$

3. Calculating the contribution of each rule:

$$\mu(y) = \min\left(\alpha_i(x)\ ,\ \mu_{\mathbf{B}}{}^{i}(y)\right). \tag{6}$$

4. Aggregation rules:

$$\mu(y) = \max_i\left(\mu_{\mathbf{B}}{}^{i}(y)\right). \tag{7}$$

5. Calculating the crisp value of the output:

$$y = \frac{\int u\mu(u)du}{\int \mu(u)du}\,. \tag{8}$$

If we use a discrete space, we obtain:

$$y = \frac{\sum_k u_k \mu(u_k)}{\sum_k \mu(u_k)}\,. \tag{9}$$

This implementation is called «min, max, barycenter». Where min stands for minimum function, max for maximum, n is the number of inputs whereas N is the number of different linguistic fuzzy sets for each input.

3 MODULAR DESIGN

3.1 Problem Description: Identified Parameters and Cell States

Due to the dynamic and complex nature of wildfire, it is impossible to identify, capture and model all influential parameters with absolute accuracy [Iliadis, 2005], [Rothermel, 1972], [Grishin, 1997], [Iliadis et al, 2002].

Three parameters groups determine the fire spread ratio: vegetation type (caloric content, density...); fuel properties (vegetation size) and environmental parameters (wind speed, humidity and slope...) [Papadopoulos, 2010], [Ameghino et al, 2001]. The flaming fire evolves/moves according to the direction of the wind, its velocity and the relative humidity.

In order to test our approach, we have chosen two main variables: wind speed and relative humidity. The wind speed is provided by the Beaufort scale measurements which is an empirical measure based on observed conditions. The humidity influences the wildland fire behavior by increasing the risk factor. Low relative humidity is an indicator of high fire danger. A dry and powerful wind, associated with a dry ground, enormously increases the fire propagation [Bisgambiglia, 2008].

Firstly, we distinguish five possible states that a cell can take. Each cell represents a limited area of the forest:

- Nonflammable area (N): It can be a road, a surface of water or just an empty surface;
- Unburned area (U): It is a passive state; it represents any fuel which is not consumed yet by fire;
- Burning area (B): represents a consuming fire;
- Ember area (E): A small, glowing piece of coal or wood, as in a dying fire;
- Ash area (A): It is afterburning state; it is the final combustion process state. At this stage, the nonvolatile products and residue were formed when matter is burnt.

3.2 Atomic Model for Cellular DEVS Fire

The fire spread is defined as the propagation process that all burning cells ignite their unburned neighboring cells. The fire area is modeled as a cellular space, and each cell corresponds to a sub-area of the fire.

The fire area is represented as a 2D cell space of 200 by 200 rectangular cells whose dimension depends on the resolution of the spatial data. Each cell represents one atomic model which is linked to 8 neighbors to form a coupled model. Nearest neighbors are defined as grid

[Wainer, 2009]. We use the ignite event I as an input port for each atomic model.

Figure 4 depicts an atomic model which is composed of five basic states. Each atomic model represents a current cell. Each cell DEVS specification is defined by (1) with:

X={(W,*w*),(I,*i*),(H,*h*)}
Where W,I,H represent respectively the input ports i.e. Wind, Ignition, and Humidity, whereas *w*, *i* and *h* correspond to the value taken by these ports;
S={*N*,*U*,*B*,*E*,*A*};
Y={(I,*i*)};
$\delta_{int}(B)=E$, $\delta_{int}(E)=A$;
$\delta_{ext}(U,e,W?w)=B$, $\delta_{ext}(U,e,I?i)=B$, $\delta_{ext}(U,e,H?h)=B$;
$\lambda(B)=I!i$, $\lambda(E)=I!i$;
$t_a(U)=\infty$, $t_a(B)=\tau$, $t_a(E)=\tau$, $t_a(A)=\infty$.

Where t_a: stands for time advance function, it represents the lifetime of states; τ: is calculated by (10):

$$\tau=\text{FIS}(\mathbf{X}). \qquad (10)$$

Where τ is a fuzzy lifetime obtained by the fuzzy inference system. This fuzzy controller gives us the lifetime of each state of our model. The t_a function is then modified by including the fuzzy controller value obtained via the relationship between the input values and the duration of the current state. This approach corresponds to our contribution.

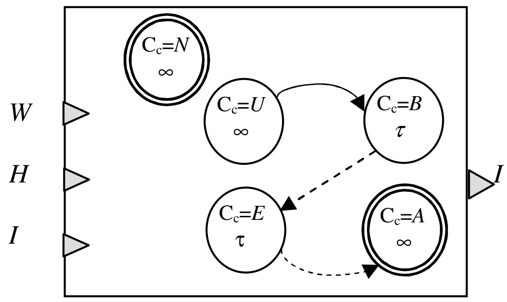

Figure 4: Cellular DEVS Fire atomic model

3.3 Reasoning Process

According to our model (Figure 4), we note H the relative humidity parameter, whereas W the wind velocity. The fuzzy logic controller describes the structure of the fuzzy rules as follows:

Rule$_i$: **<u>If</u>** *H* is **A** **<u>and</u>** W is **B** **<u>Then</u>** τ_f is **C** (11)

Where A, B and C are linguistic variables and τ_f stand for fuzzy lifetime.

The different variables are fuzzified as below (Figure 5):

The parameter H is divided into three fuzzy sets (linguistic term): Dry (D), Little humidity (L), and too Much humidity (M). The wind velocity is also fuzzified into three subsets: Calm wind (C), a Slight one (S) and a power wind (P). The output parameter τ_f is fuzzified into three fuzzy sets: Slow time (S), Medium time (M) and Fast one (F).

The universe of discourse of each variable is given by:

- *H*: its values belong to [0%, 100%];
- *W*: based on Beaufort scale;
- τ_f: The firefighters estimate the flaming front propagation rate at approximately 3 to 8% of the wind speed [Bisgambiglia, 2008].

The fuzzy rules base is given by Table 1. This table is based on empirical reasoning of firefighters.

H / W	/D	L	M
C	M	S	S
S	F	M	M
P	F	F	M

Table 1: Fuzzy rules table

According to min-max barycenter method used by the fuzzy controller, we calculate the mean lifetime of each state. The obtained value is then passed to the simulator.

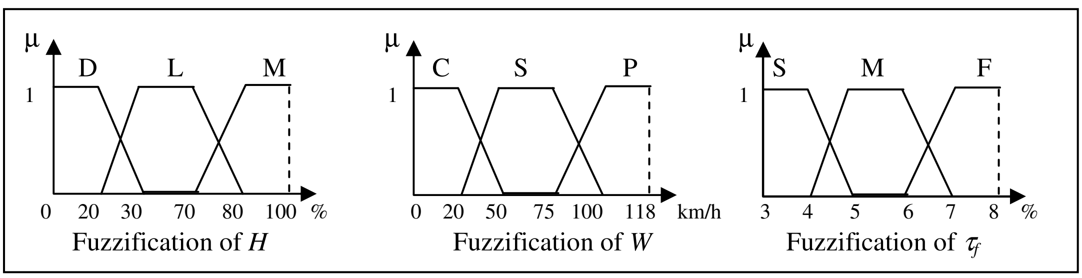

Figure 5: Fuzzification of variables H,W and τ_f

3.4 Architecture and Framework

The proposed architecture is a classical DEVS framework. Our challenge was to keep the DEVS formalism unchanged and to improve it without modifying its components.

So our architecture is based on an atomic model which is associated to a simulator. Our contribution is the addition of the FIS module whose function is to assess the lifetime of each state according to the input parameters Wind and Humidity (Figure 6).

Initially, we fill the fuzzy rules table based on firemen reasoning; after we get the different observed values into the fuzzy inference system in order to evaluate the state lifetime parameter according to the values taken by the variable W and H.

Each cell represents an atomic DEVS model which is associated to one simulator. The dynamic system of the flaming front propagation speed is given by the simulator. It is based on the current cell position, τ and the wind direction.

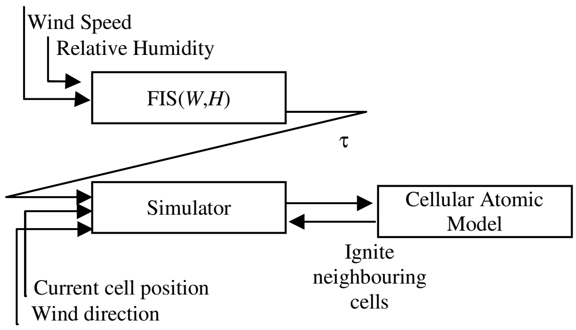

Figure 6: Model framework

4 SIMULATIONS AND RESULTS

4.1 Experimental Design

In these simulations, we have considered these parameters as follows:

- Wind speed w_s: Its value is 10 km/h, which represents the number 2 in Beaufort scale (slight breeze);
- Wind Direction: Southerly wind, it blows from the south to the north;
- Humidity coefficient: Wet (85%);
- Wildland: Closely spaced;
- The propagation velocity is obtained via the fuzzy controller. For each cell, τ is evaluated by equation (10);
- The virtual forest is constructed as a grid of 2000x2000 cells where each cell represents an area of 2.5×2.5 m² (c_l=2.5m) which is the spatial resolution of ALSAT.2A satellite. The total area is 2500 ha.

As mentioned previously, we assume that uniform parameters characterize the cell space, i.e. the direction and wind speed are constant along the forest fire area, also for the humidity factor. The Figure 7 represents some simulation results in different time periods.

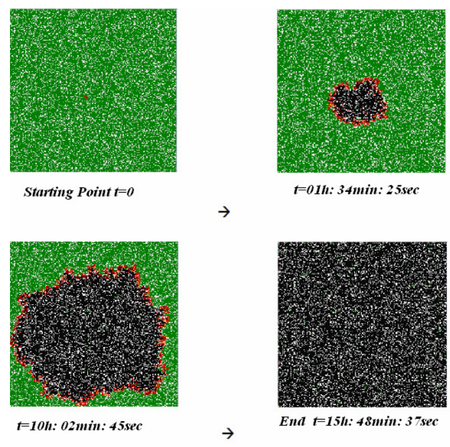

Figure 7: Wildfire spread evolution

We have also calculated the burned area during this simulation. The Figure 8 depicts the evolution of this process.

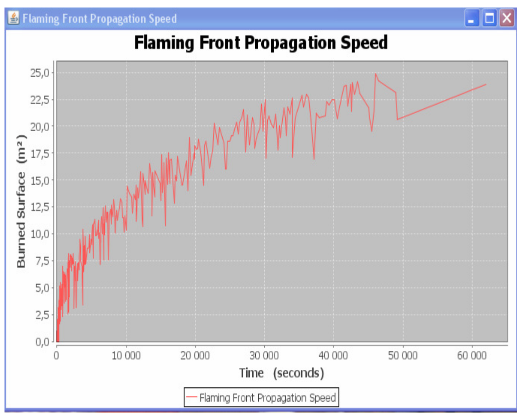

Figure 8: Flaming front propagation speed

4.2 Results and Discussions

As we can see with equations (4) through (8), and according to table 1, the alone fired rule obtained is:

If H is **M** **and** W is **C** **Then** τ_f is **S**

The corresponding fuzzy lifetime obtained is illustrated on Figure 9.

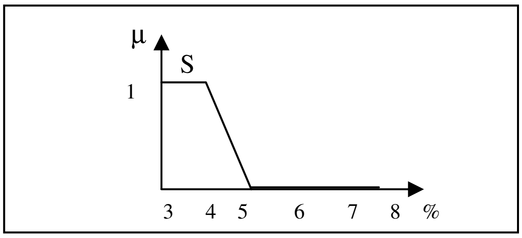

Figure 9: Fuzzy Lifetime state τ_f

After defuzzification, we obtain a numerical value τ_f.

τ_f=FIS(W,H) =3.64%

This value is of course obtained according to the values given in paragraph 4.1

Now we can calculate the state lifetime by this equation:

$$\tau = \frac{100 \times c_l}{\tau_f \times w_s}. \qquad (12)$$

Where w_s is wind speed and c_l is the cell length

This outcome seems explicable. In fact, with the above conditions, a firefighter assesses the fire propagation rate to 3% whereas our approach is close to this result (3.64%).
A comparison between the classic DEVS and the proposed method is presented in table 2.

Factors	Classic DEVS	Proposed Approach
τ_f	3 %	3.64%
Burning Time	16h: 29min: 15sec	15h: 48min: 37sec

Table 2: Comparison results

Although this result is explained, it seems simpler to obtain the state lifetime using the fuzzy logic theory. Its simplicity provided us a new method to overcome the difficulty to estimate for each state its duration.

It is important to test this method on physical and natural process in real time evolution to measure the improvement of this approach.

5 CONCLUSION AND FUTURE WORK

This work investigates how discrete event simulation DEVS can be used with fuzzy logic for handling fuzzy lifetime parameter of state in DEVS specification.

A new approach was developed without modifying the core of DEVS formalism and introducing the concept of fuzzy lifetime by showing the relationship between the input values and the duration of the states.

This paper has allowed us to combine fuzzy approach and DEVS formalism in wildfire spread simulation.

Initially, we review some concepts on DEVS formalism and fuzzy logic controller. A focus on DEVS formalism was done. An outline of fuzzy inference system was developed and the last point was the presentation of our approach and its implementation.

Through these work we showed that it is possible to use our approach to model the intuitive reasoning of the professionals. We have adapted the DEVS formalism by taking into account uncertainties without modifying the structure of the classic DEVS specification.

For that it was necessary to identify the relevant parameters. They were considered important only by their degrees of influence on the phenomenon. The most significant parameters for the wildfire spread are those having the most influence on the fire; these parameters are wind, its direction and humidity rate.

Hence, the resulting application is a simulator of forest fire propagation, integrating imperfect data. However, the subject is not ready to be completed. Many other parameters still remain to be integrated (temperature, topology of the ground, inflammability, heights of the vegetation…) in order to improve quality of simulation and get more realistic results and consequently the model must be more complete.

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