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Event Triggering Estimation for Cell-DEVS

Wildfire Spread Simulation Case

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***Abstract*—This paper aims to estimate the trigger event in the DEVS formalism by the Bayesian networks. To validate this approach, we develop a simulation tool for wildfire spread which could be used as decision making for fires control and containment. In fact, this work attempt to foster the integration between two concepts: Bayesian networks, known as powerful tools for representing uncertain events, and the DEVS formalism, a discrete event simulation formalism known by the modeling process of complex natural systems. Thus we have introduced Bayesian networks to show up fire spread graph and the probability of states transitions can be calculated by the use of the joint probability distribution. This probability is then introduced to the fire spread Cell-DEVS model in order to simulate wildfire propagation.**

The present paper stated as follows: Firstly we introduce the wildfire spread phenomena; we follow by describing some closely related works. After, we present the specification formalism DEVS and some of its extensions, then, we introduce Bayesian networks. Our approach is then presented and some simulations are done. At the end, we conclude this work with a conclusion and perspectives.

Keywords-Modeling and Simulation; Discrete Event Systems Specifications; Cell-DEVS; Bayesian Networks; Wildfire Spread Simulation

I. INTRODUCTION

The natural disasters (fires, floods, tsunamis, hurricanes...) have a considerable human and economic cost. The annual economic losses combined to catastrophes over the world rose on average to 75.5 billion dollars in the Sixties, to 659.9 billion dollars in the Nineties [1]. Their increases these last years reinforce the need to step up prevention, fight and control.

Nowadays, the modeling and simulation formalisms are more and more used in order to help to forecast and understand these complex phenomena. Nevertheless, these phenomena are very complex to study due to the great number of parameters taken in consideration. In the majority of the cases, these parameters remain uncertain and inaccuracy.

The lacks or partial knowledge on certain systems, cause this fact of uncertainty. This point was studied by some theories amongst them, the probability theory which remains an approximate but effective means to define complex systems or misdiscribed ones. The result of this approach has more chances to be coherent according to objectives and constraints of the system.

On the other hand, simulation manages models in order to produce behavioral data, i.e. to evolve/move the states of the model over time [2]. Simulation is then similar to experience [3][4], given the possibility of predicting the behavior of complex systems.

The focus of our work refer to the development of a cellular specification system described by the discrete event system specification (DEVS) combined with Bayesian networks in order to simulate forest fires growth including uncertainty in inputs data.

II. LITERATURE REVIEW

The well-known applications are FARSITE [5] and BehavePlus [6][7][8]. Both are based on the analysis of experts and professionals of forest fires domain.

Many other works were directed in this field, among them, we can cite: SiroFire [9], HFire [10], Prometheus [11], PyroSim [12]. Each one differs from the other by, the nature of the affected data (vegetation, atmosphere, topography…), studied behaviors and models [13]. Others have treated the fuzzy character of the system entries [14][1], whereas some tried to formalize the problem by a precise mathematical model instead of its complexity [15][16][17].

To give a convivial aspect, certain researchers tried to add the real-time aspect to this application aided by geographic information system GIS and defining a dynamic structure space [13][18][19].

III. SUBSET OF CURRENT THECHNIQUES

A. The DEVS Formalism

1) Introduction

The DEVS formalism "Discrete EVent system Specification", was introduced by Professor B.P. Zeigler [20]. It is based on mathematical theory of dynamic systems [2]; it is a reference for coupling heterogeneous models. In

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fact this formalism is adapted to a great number of applications [21].

The DEVS formalism is a hierarchical and modular modeling approach, centered around the state concept. In its basic form, it does not take in account the system structure evolution; only the states can evolve/move [1].

Each system is described by two points: functional (behavioral) and structural aspect [22]. Likewise, DEVS formalism is composed of two types of models: atomic models and coupled models [2]. The atomic model represents the basic behavior of the system whereas the coupled model, its internal structure.

2) Atomic Model

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

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

Where
X: input events set;
S: states set;
Y: output events set;
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;
$Q=\{(s,e) \mid s\in S.0\leq e\leq t_a(s)\}$: 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: $S\rightarrow\Re^+$: time advance function, it is the lifetime of the state.

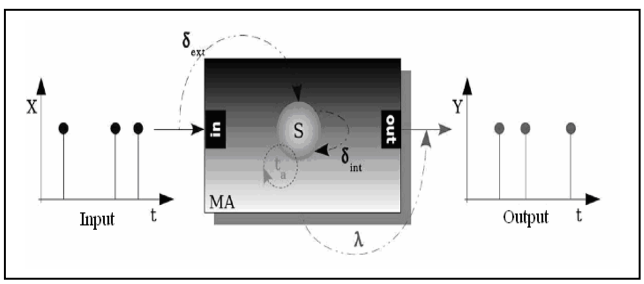

Figure 1. DEVS atomic model semantics

3) Coupled 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):

$$CM=\langle X_{self},Y_{self},D,\{M_d \mid d\in D\},EIC,EOC,IC,select\rangle \quad (2)$$

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,
$M_d \mid d\in D$: 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

4) DEVS Variants

While studying complex natural systems, it is frequent that a certain number of parameters are imperfectly defined. To deal with this problem, the multi-formalism DEVS provides several extensions making it more flexible [22], [23]. These extensions have consequently acts either on the transitions functions, or the states and their lifetime. In both cases, these changes modify the structure of the models and/or the simulation algorithms.

The following list is not exhaustive of DEVS variants. We note Fuzzy-DEVS [24], Min-Max-DEVS [25], iDEVS [1], Cell-DEVS [26] and Parallel DEVS [27]. These extensions handle inaccuracy and uncertainty property of events and states. Uncertainty intervenes on the states changes level, whereas the inaccuracy intervenes either on the state lifetime or the event values.

These last years, the cellular models gained in popularity [28] especially the cellular automata [29]. They can be defined as being an infinite N-dimensional lattice of cells whose values are updated according to a local rule. This update is made simultaneous and synchronically for each cell and its neighborhood [30].

However, the cellular automata require usually very high times computing, mainly due to their synchronous nature. The variant Cell-DEVS solves this problem by employing DEVS formalism [23], [29]. Cell-DEVS extended the formalism of DEVS to represent the cellular models. Each cell is defined as an atomic model whereas the cell space is represented by a coupled model.

B. Bayesian Neworks

1) Overview

The human been environment is difficult to describe, precisely, when we lack the necessary resources to deal with imperfect data or partial knowledge of complex system. It is a tough problem to treat uncertain and inaccurate parameters with a precise mathematical theory, so we need an estimation to assess theses parameters and the well-known theory which copes with that is the probability theory.

Bayesian network is a probability distribution; it combines two theories, the probability theory and the graph theory [31]. A Bayesian network is a Directed Acyclic Graph (DAG) composed by Nodes and Edges. Nodes express random variables whereas Edges represents influences between them.

2) Graphical Notation

The complete specification of a Bayesian network requires to specify, on the one hand its structure (DAG), and on the other hand, its parameters (probability distribution table). To realize that, we can use two possible approaches: human expertise or machine learning [32].

In the expertise case, network structure definitions begin by identifying the possible nodes and the distinction between informational variables (observable) from hypothetical ones (non-observable). The probability relationships between them are referred to as the observation model [33].

For each variable, we associate a node and edges represent both causal relationships and conditional independence relationships "Fig. 2".

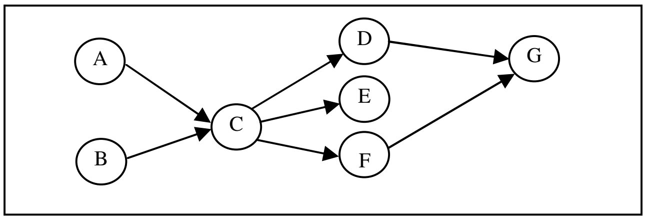

Figure 2. Example of a Bayesian Network

3) Conditional Independency

Two distinct variables A and C are d-separated if, for all paths between A and C, there is an intermediate variable B such that either "Fig. 3":

- Connection is serial or diverging and B is instantiated or,
- Connection is converging (V-structure) [32], [34].

If A and C are not d-separated, we call them d-connected.

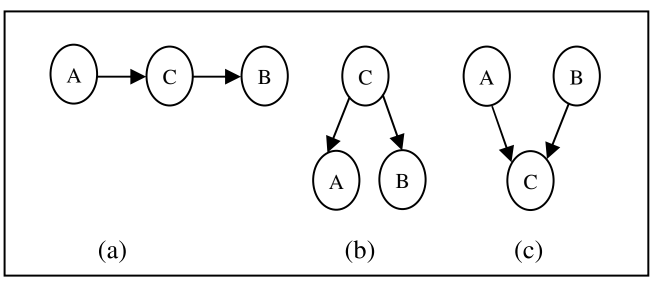

Figure 3. Basic structure of Bayesian Networks

The corresponding probability can be given by (3)-(6):

- Serial case "Fig. 3 a"

$$p(B|C, A) = p(B|C) = p(B|\text{parents}(B)) \quad (3)$$

- Divergent case "Fig. 3 b"

$$p(B|C, A) = p(B|C) = p(B|\text{parents}(B)) \quad (4)$$

- Convergent case "Fig. 3 c"

$$p(C|A, B) = p(C|\text{parents}(C)) \quad (5)$$

with

$$p(A|B) = \frac{p(A \text{ and B})}{p(B)} \quad (6)$$

The joint probability of n random variables $X_1, X_2, \ldots, X_n$ is:

$$p(X_1, X_2, \ldots\ldots, X_n) = \prod_{i=1}^{n} p(X_i|pa(X_i)) \quad (7)$$

Where $pa(X_i)$ is set of parents of the random variable X_i on the graph. The conditional independence relationship encoded in a Bayesian network can be stated as follows: a node is independent of its ancestors given its parents.

IV. APPROACH AND METHODOLGY

A. *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 [14], [15], [16], [35].

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...) [36]. 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, it is an empirical measure that relates wind velocity to observed conditions at sea or on land; whereas 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 increase the fire propagation [1].

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.

B. Bayesian Model for Wildfire States Transitions

The model presented in this part describes in a data-processing way the empirical reasoning of the firemen of the Departmental service of Fire and Help (SDIS) of Haute-Corse France [1].

- On the grounds of the South of France, and with homogeneous vegetation, a fire growth as spreading elliptical wave, following the wind direction.
- The firefighters estimate this propagation at approximately 3 to 8% of the wind speed according to the characteristics of the ground (slope, density and nature of the vegetation).
- A hot, dry and powerful wind, associated with a dry and inclined ground, enormously increase fire growth probability.
- The wind has a more influence on the fire propagation than humidity.
- The wildland for the studied area is assumed uniform and is represented by a constant coefficient.
- The neighborhood list depends on the wind speed and its direction.

Many parameters characterize forest fire propagation. All of them are related to each others and in the major case are sullied with uncertainty and inaccuracy. Let take an event, inaccuracy can intervene either on the time or value. Hence, inaccuracy is relating to its value while uncertainty concerns its realization. The use of Bayesian networks is thus appropriate for such problem.

For simplicity's sake, we suggest to consider two parameters for wildfire spread in order to test our approach: wind speed (W) and relative humidity (H) "Fig. 4". In this figure, C_c means the current state whereas C_n the neighbor cell. $p(C_n=B|C_c=B)$ is conditional probability that is, given that the event C_c is Burning has occurred, or will occur, the probability the C_n will in Burning state will also occur; whereas p_W is prior probability that is Windy day.

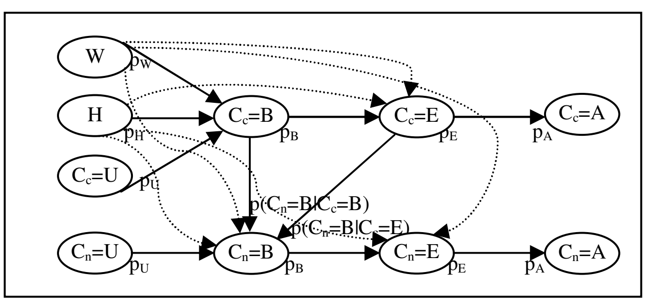

Figure 4. State transitions Bayesian network model

We assume that the environmental parameters are uniform over the whole simulated space.

C. Coupled 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 coupled model. Nearest neighbors used for square Geometry [23], we use the ignite event I as an input port for each atomic model.

The coupled model is a combination of two cells (atomic model) "Fig. 5". The left AM represents the current cell whereas the right one is the nearest cell. Each cell DEVS specification is defined by (1):

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

Where t_a: lifetime of states; τ: is calculated by (8):

$$\tau = \frac{100 \times c_l}{5 \times w_s} \qquad (8)$$

Where w_s is wind speed and c_l is the cell length

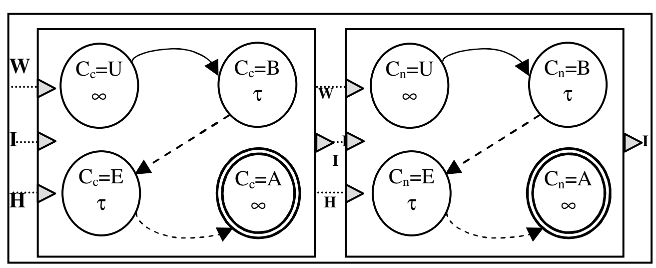

Figure 5. DEVS Coupled Model

V. Simulations and Results

A. Experiments Design

Our simulation model is based on two modules: Event estimation module and atomic model DEVS “Fig. 6”. The first module presented in the graph assesses the different parameters of the fire growth significant factors. This assessment is based on probability distribution table extracted by empirical reasoning of firemen.

Initially, we fill the probability distribution table based on firemen reasoning; after we present the different observed values to the Event Estimation module whose function is to estimate these parameters.

Each cell represents an atomic model DEVS in the simulation model. It performs its local computation of the possible ignited neighboring cells based on the estimated events W, H and I, the computed parameter τ (8), wind direction and current cell position “Fig. 6”.

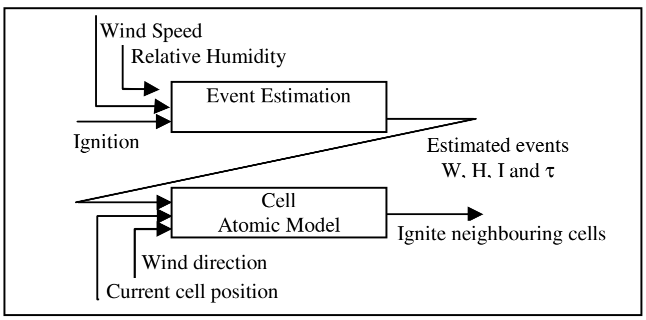

Figure 6. Simulation Model for Event Triggering Estimation

B. Experiments Results

For this example we will define these parameters as following:

- Wind Force: Slight breeze, it corresponds to number 2 in Beaufort scale (5 to 11 km/h);
- Wind Direction: Southerly wind, it blows from the south to the north;
- Humidity coefficient: Wet (85%);
- Wildland: Closely spaced;
- The propagation velocity is considered constant. We suppose that it is equal to 3% of the wind speed. This percentage is the lowest value given by the SDIS;
- The virtual forest is constructed as a grid of 200x200 cells where each cell represents an area of 2.5×2.5 m² (6.25/ m²) which is the spatial resolution of ALSAT.2A satellite. The total area is 250.000 m².

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 “Fig. 7” represents some simulation results in different time periods.

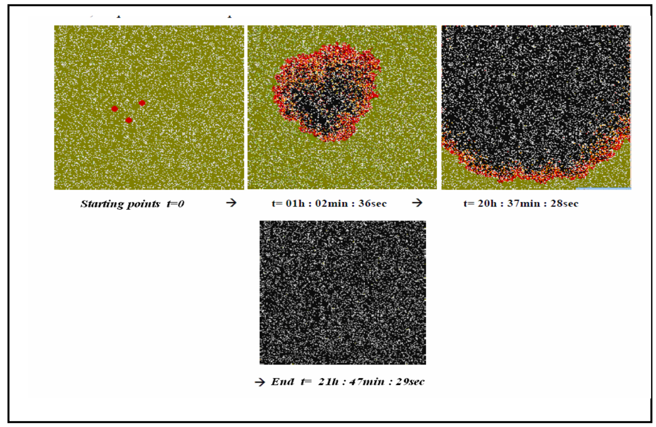

Figure 7. Wildfire spread evolution

We have also calculated the burned area during this simulation; the “Fig. 8” depicts its evolution.

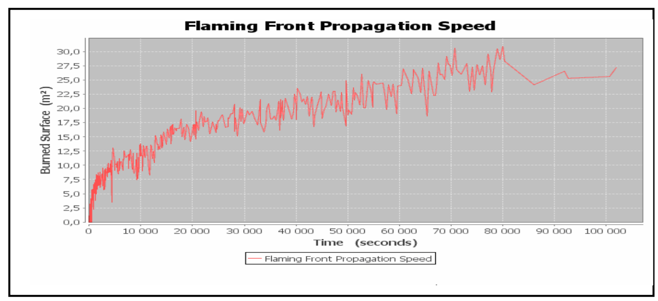

Figure 8. Flaming Front Propagation Speed

VI. Conclusion and Perspectives

This work investigates how discrete event simulation DEVS can be used with Bayesian networks for handling uncertain parameters for wildfire spread framework.

Initially, a state of the art was given on the topic, followed by a brief definition of modeling and simulation paradigms. A focus on DEVS formalism and its extensions was done. An outline of Bayesian networks was developed and the last point was the presentation of our approach and its implementation.

Through this work we showed that it is possible to use our approach to model the intuitive reasoning of the professionals and implement it by using an adapted tool like DEVS formalism. Taking into account uncertainties in state transitions allow providing a tolerable simulation result. The result is certainly vague, but has more chance to be interpreted correctly.

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

However many others factors need to be taken in consideration to see the real influence of each of them and consequently the model must be more complete, nevertheless, the resulting application is a simulator of forest fires propagation, integrating imperfect data. Hence, 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.

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