

Hybrid and Evolutionary Agent-Based Social Simulations Using Lévy Flight as Randomization Method

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Abstract—The use of Agent-Based Social Simulations (ABSS) using random-walk algorithms as the randomization approach in an attempt to reproduce human behaviors abound in the literature. However, almost all human actions are nonrandom and include a probabilistic component. This work investigates the use of a probabilistic distribution-based randomization method based on *Lévy flight* as an improvement to the use of traditional random-walk algorithms in cognitive agent models. The fact that Lévy flight has been shown to be a more suitable approach than random walk in mimicking natural phenomena, encouraged us to assess whether it could be a more robust randomization method in our agent-based social simulations. Experiments were carried out using Lévy flight as the randomization method in our new hybrid evolutionary agent model for ABSS, modeling a realistic scenario of the spread of dengue fever. Previous papers proved that this kind of agent models, which incorporates two components namely, genetic and cultural layers, produce good simulations results. The aim here is to assess whether there is qualitative and quantitative predictive power of the model. This paper looks at the following decision components variations together with the new randomization method: (i) agents only with genetic component; (ii) agents only with cultural component; and (iii) agents with both genetic and cultural components. The results show the beneficial impact in Lévy flight that leads to better prediction in all combinations of decision components.

I. INTRODUCTION

Agent-based social simulations (ABSS) have been widely used by social scientists to understand real social phenomena. The major motivation for using agent models in social simulations is the possibility of modeling and controlling different granularity levels during the simulation process—Epstein and Axtell have provided many reasons for using agent-based models instead of the analytical ones [1].

Many platforms and models have been proposed to support ABSS, e.g., the Schellings Segregation model [2], the Garbage Can model [3], the Sugarscape model [1] and the Vidya platform [4], [5], [6]. In previous works, we introduced the PAX (Plausible Agents Matrix) framework [7], [8], whose main objectives are to facilitate the development of social simulations which can consider the modeling of spatial structuring elements [9]. The PAX Framework is used in this paper for performing our experiments.

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In 1947, the French mathematician Paul Pierre Lévy proposed a new type of randomization method based on a specific kind of probability distribution: heavy-tailed. The proposed method has been shown to be useful in simulations for random or pseudo-random natural phenomena like: animal scan paths, searching food problems or earthquake data analysis. It has also been used to model data exhibiting clustering aspects. Today it is generally understood that human mobility patterns are non-random [10]. One of the first works in this direction was done by Rhee *et al.* [11] who investigated the Lévy flight nature of human mobility using real data. Brokmann [12] later introduced a phenomenological model for the generation of human scan path. Brokmann's experiments showed that some human behaviors can be better modeled as Lévy flights.

In this article, we investigate the impact of Lévy flight as randomization method in our new hybrid evolutionary agent model [7]. The experiment combines the Lévy flight method with two devised evolutionary perspectives: (i) *genetic* in which agents have genetic codes that influence their behavior, and (ii) *cultural* where agents have a belief system that also influences their behavior. The Lévy flight method is applied on both the agent's walk algorithm and agent's decision mechanism, mainly, to create an "inertial effect". When an agent decide to take an action (actions change the agent internal state) the probability to remain on this state is high and decreases over time.

Our results show that the new model improved the simulation results of a real town in the countryside of the Pernambuco state (Northeast of Brazil). We use different configurations for the tested model, performing a comparative analysis between simulated and real data.

II. PAX FRAMEWORK

As in our previous works, we built our model and perform all simulations using the PAX (Plausible Agent Matrix) Framework. Its architecture was conceived to be as modular as possible, allowing social scientists to model and perform ABSS including the following elements:

- Environments: structures, structural levels and environments cell's labels;
- Entities: the basic elements of simulations, defined by a set of spatial characteristics;
- Entities' interaction interfaces: that can be invoked by agents to interact with others;
- Agents: abstract structures to implement context-specific agents.

A. Environment

In PAX, the environments are 2-dimensional lattices defined by different types of elements: structural levels, structuring elements and labels for the environmental cells. All structures in PAX are entities with spatial coordinates (i.e. placement), dimensions (i.e. width and length) and may also contain other structures in it. The placement of structures in the environment (i) allows different agents' strategies, (ii) may influence the choice of strategies, and (iii) may work as means of promotion of global order, including the creation of beneficial contexts that may impact the dynamics of social networks.

B. Entities

Entities are anything that can be conceivable as part of the environment. They contain a set of 2-dimensional spatial coordinates, their meta-location (i.e. the structure where they are located which may be "none") and an entity interaction interface. As the basic class of the simulator, they are used by the user (i.e. the social scientist) to create context-specific objects. They allow for the implementation of some abstract methods and the provision of an entity interaction interface (if necessary).

C. Entity Interaction Interface

An entity interaction interface represents a set of rules that guide the way entities interact with each other. For this, an entity interface incorporates a set of possible actions that entities can perform on other entities and their state; restrictions may be placed based on the current state of the entity. Therefore, when a user is designing an object and wants to include restrictions on its behavior during interactions with other entities, he only needs to implement an entity interaction interface.

D. Agent

In the framework, agents are entities designed to be intelligent. Nevertheless, the framework does not supply any particular implementation of intelligent components for the agents' behavior. However, PAX provides an abstraction for perception and action, leaving it open for the developer to include intelligent processing routines. Therefore, the user, when implementing a specific kind of intelligent agent, is free to build an intelligent module, mapping perceptions to actions according to its needs (regarding behavior).

III. LÉVY FLIGHT

Lévy flight is a kind of random algorithm. Its increments are distributed according to a *heavy-tailed* probability distribution. One example of heavy-tailed probability distribution, also known as Lévy distribution, can be represented by

$$f(x; c) = \sqrt{\frac{c}{2\pi}} \frac{e^{-c/2x}}{x^{3/2}}. \quad (1)$$

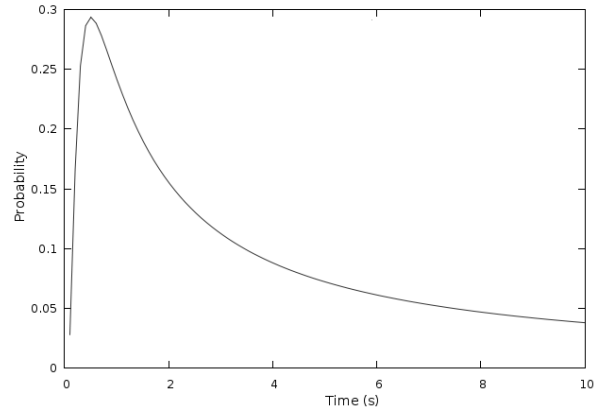


Fig. 1. Example of a Lévy probability distribution with $c = 1$

Equation 1 represents a probability distribution in which the probability decrease over time according the scale parameter (c). Figure 1 shows an example of the distribution for $c = 1$.

A Lévy flight is classified as a Markov process. In Markovian processes, the future state of an object depends only on the object's present state and a limited number of past states. As a Markovian process, Lévy flight makes the probability of an object stay in the same state decrease over time.

Lévy flights have been used as fundamental key to improve algorithms in many fields of computing science. Terdik and Gyires [13] propose Internet traffic models using Lévy flights instead Poisson distributions. Other works ([14][15]) describe evolutionary algorithms which use mutations based on the Lévy probability distribution. Hoofar *et al.* [16] investigate Lévy flights based evolutionary algorithms in optimization of selected antenna problems. In 2008, Rhee *et al.* [11] investigated the Lévy flight nature of human mobility. Rhee *et al.* based their study on real data. They installed GPS (Global Positioning System) on 44 volunteers in various outdoor settings including two different college campuses, a metropolitan area, a theme park and a state fair in order to get real data on human mobility.

In this article, we investigate the use of Lévy flights as a mobility algorithm as well as the agent state-transition inertial effect for our hybrid evolutionary agent model.

IV. AGENT MODEL

In this paper, we use the hybrid evolutionary agent model as proposed in Lima Neto *et al.* [7]. We argue that this model is evolutionary because the agents' learning is based on evolutionary processes and it can be considered hybrid because it combines two different evolutionary approaches (genetic and memetic). The architecture organizes the agent decision engine in two main concurrent components that combined enable agents to choose the appropriate action for each state of execution:

- Cultural Component: Responsible for the agent cultural learning. This means that an agent can modify its behavior through life learning and that the acquired

knowledge can be disseminated to other agents in the society using available communication media. The cultural component enables both individual and social learning, since beliefs can be disseminated in the society and can be useful for solving problems that require participation of groups of individuals.

- **Genetic Component:** This component is immutable throughout the agent’s lifetime—changes take place between generations. It is composed of the genetic traits passed on by the agent’s ancestors perpetuating successful behaviors via a process akin to natural selection. The genetic component has a genotype which quantifies the agents attributes and represents some of its behavioral tendencies.

We applied the Lévy-flight randomization to two layers in the agent model:

- **Agent-walk algorithm:** the direction of movement changes following a Lévy distribution.
- **Agent-decision mechanism:** adds an inertial effect in the state transition process.

The main difference between the traditional random walk randomization and Lévy flight randomization is showed in Figure 2. In this figure the agent walks 5000 steps forward starting at (0, 0) point. In the real world, people rarely walk without a fixed direction; visiting random places between the source and destination locations (as it happens in the random walk place). This characteristic makes the new approach to agent movement more realistic because it decreases the number of random locations visited between source and destination.

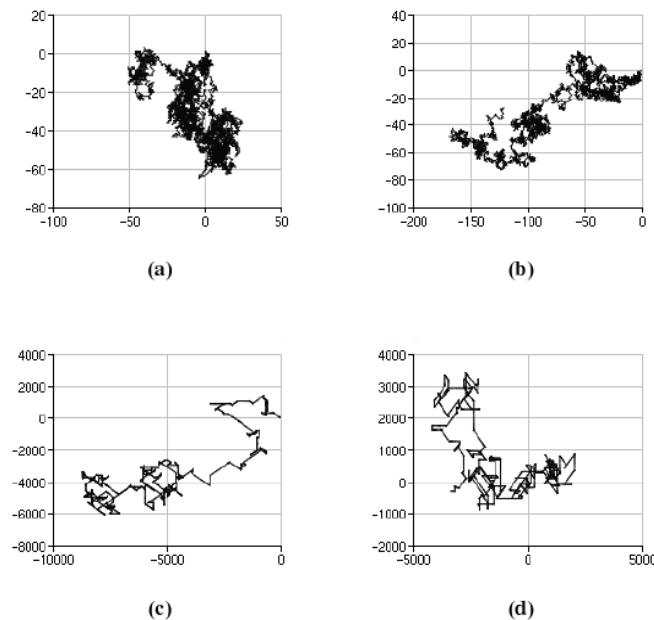


Fig. 2. 2D representation of agent walk algorithm comparing Lévy flight and traditional random walk algorithm. (a) and (b) agent uses random walk; (c) and (d) agent walks based on a Lévy flight.

An agent without the inertial behavior (provided by the Lévy flight) change its internal state several times in an iteration. In fact, an agent internal state transition is a high cost operation for the simulation (each iteration updates all agents’ internal state). Using traditional random walk as randomization algorithm the agent changes its internal state in all iterations whereas using Lévy flight its state changes according a Lévy probability distribution. This approach approximates the agent model to the real human behavior as we will show with our experiments.

V. CASE OF STUDY

In our previous work, we used the PAX framework to simulate a real environment investigating the hybrid evolutionary model [7]. In that study we simulated a generic epidemic on some scenarios, aiming to assess their yield impact to the epidemic. Regarding the modeling of environments, this work innovates by applying the Lévy flight randomization in the agent’s walk algorithm and as inertial factor on agent’s state transition.

A. Modeling the Town of Iguaraci

In this work, we have simulated Iguaraci, a small Brazilian town located in the Northeastern state of Pernambuco. Real data was collected from the database of the state government - BDE/PE (at <http://www.bde.pe.gov.br>) and from demographic data from the Brazilian Institute of Geography and Statistics - IBGE (at <http://www.ibge.gov.br/english>). Iguaraci has an area of approximately 780km², and a population of approximately 12,000 inhabitants, giving us a population density of ~ 15 per km².

In the simulated environment, we have represented Iguaraci as a square grid of cells of cardinality 28×28 ; each cell corresponds to 1km² of Iguaraci. Based on real geographic aspects of the town, the environment was divided in 4 structured regions, each representing one of the communities in the city—2 large and 2 small communities, based on their density of (22 citizens/km²) and (5 citizens/km²) respectively. As we are simulating dengue fever spread over the population, we also placed in the environment health structures, i.e. hospitals and health centers. Iguaraci has 1 hospital and 3 health centers, but these structures are not sufficient to attend all the demand for health services. Hence, the population has to use health services of two neighbor towns: Afogados da Ingazeira and Sertânia. For this reason, two additional hospitals were considered in the model, representing the Hospital of Afogados da Ingazeira (19km away) and the Hospital of Sertânia (46km away). These two towns are connected to Iguaraci by a state road, PE-292. These elements are all illustrated in Figure 3. All data used in the simulation was collected from the aforementioned sources at the beginning of 2007.

B. Modeling Agents

In the environment described above, 12000 agents were added, each one with an infection and a well-being label. The former represents the health status of the agent (i.e. if

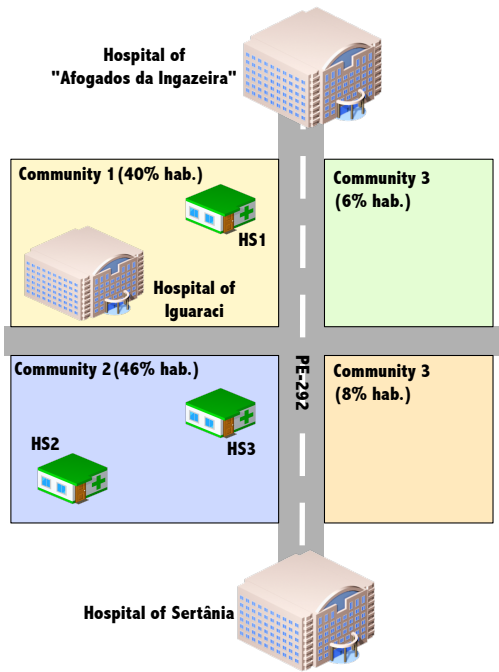


Fig. 3. Schematic view of the environment used in the simulation.

the agent is infected or not by the dengue fever), and the latter informs if the agent is feeling good or feeling sick, regardless of its health status. Even if the agent is not infected, its well-being label may be set to sick. However, if the agent is infected, it always feels sick. The decision to go or not to a health unit is based on the well-being label, not in the health condition by itself. This is a hedonistic perspective that most humans naturally subscribe to.

In previous works [7], [17], we assumed that each agent in the simulation perform 5 actions in one day, thus the simulated day has 5 iterations. Total simulated time period was 1825 iterations, representing 365 days in the real world. For this work the state transition process is distributed according a Lévy distribution.

The learning module of the agent in this hybrid evolutionary approach is composed by cultural and genetic components. To investigate the influence of the Lévy flight behavior in each component, we simulated 3 different scenarios: (i) cultural component; (ii) genetic component; and (iii) cultural and genetic components combined. In the environment, the agent has to move to different structures according to the action chosen. To perform the action, the agent faces a cost, proportional to the distance from origin to destination. Therefore, this cost has an important role on the cultural learning component; it determines the learning reinforcement rate. The genetic component determines the probability that an agent chooses and performs an action according to its genetically coded behavior tendencies.

In the beginning of all simulations, agents do not know the best action to perform for each state. In the scenarios with cultural learning, agents learn through reinforcement learning which adjusts their behavior to their particular

needs considering their current state. An agent state is a combination of its current location and feeling. At a certain moment, an agent can be in one of the following locations: Community 1, Community 2, Community 3, Community 4, Hospital of Iguaraci, Hospital of Afogados da Ingazeira, Hospital of Sertânia, Health station 1, Health station 2, or Health station 3. The possible feeling states are “feeling good” and “feeling sick”. For each state, an agent has a set of possible actions to chose and perform. The available actions, considering all possible states are: go to one of any of the locations (above), walk inside a community, go home, and of course do nothing.

Regarding cultural learning, agents can communicate with each other and transmit their knowledge (i.e. values learned by reinforcement) to other agents. The meme transmission between two agents is the main part of the cultural evolution, since the agent shares knowledge about the best options of actions to be performed in the location where they gather at each time.

Each agent’s genetic code has the following genes:

- Gene 1 - quantify the reinforcement applied to bad and good feelings (values in the interval [100.0, 600.0]);
- Gene 2 - the tendency to accommodate at the current community (values in the interval [-1.0, 1.0]);
- Gene 3 - preference of walking inside community (values in the interval [-1.0, 1.0]);
- Gene 4 - preference for doing nothing (values in the interval [-1.0, 1.0]);
- Gene 5 - preference for going back home (values in the interval [-1.0, 1.0]);
- Gene 6 - probability of talking to others (values in the interval [0.0, 1.0]).

The Gene 1 control the intensity of the reinforcement over the actions which causes bad or good feelings. The gene 2 can assume -1.0 as value if the agent prefer to stay at the current community. The gene 3 assumes the value -1.0 if the agent likes to walk inside the current community. Gene 4 assume -1.0 if the agent prefer to remain on the same state (do nothing). The gene 5 assume -1.0 if the agent prefer going back home. The gene 6 specifies a probability to the agent interact with another agent about its experiences.

C. Modeling Dissemination Dynamics of Dengue Fever

The dengue fever is a vector-bone disease, and the dynamics of its dissemination used in the proposed model is based on the mosquito-human-mosquito (mainly *Aedes aegypti*) infection cycle. The agent infection occurs when a healthy agent is bitten by an infected mosquito. The mosquito infection is caused: (i) if a mosquito stings an infected agent (i.e. horizontal transmission); (ii) if it is descendant from an infected female mosquito (i.e. vertical transmission). Ponds and other water accumulation places are deeply connected with the disease dissemination [18].

Due to the fact of only female *Aedes aegypti* are hematophagous (i.e. are dissemination vectors), in our model only 50% of mosquitoes are able to sting the agents. In this

model, the intrinsic and extrinsic virus incubation period was abstracted away. However, all those parameters may be easily included later.

In our model, the dissemination cycle was subdivided in: (1) hatching of the eggs - the number of eggs to hatch is proportional to the number of existing eggs and the rate of water inside the cell; (2) infection dissemination - 50% of the mosquitoes inside the cell can sting the agents. The number of agents stung, at each iteration, is proportional to the number of agents and the number of mosquitoes inside the cell. If a healthy mosquito stings an infected agent, this mosquito will become infected and from now on will transmit the infection to all its offsprings; (3) mosquitoes spreading - considering that each cell is an abstraction of 1 km² of the Iguaraci area and the fact of an *Aedes aegypti* can fly up to 100m of distance, the number of mosquitoes that will fly to a neighbor cell is a function of the cell area (i.e. 1 km²), the number of mosquitoes in the cell and the maximum distance a mosquito can fly; (4) oviposition (i.e. laying eggs) - the female mosquito needs a blood meal and water to lay its eggs. Hence, the number of new eggs in the cell is a function of number of agents, amount of water and number of female mosquitoes in the cell.

The dengue disease was simulated following a Cellular Automata like dynamics. Therefore, *Aedes aegypti* mosquitoes were not represented in the model as agents, but they were abstracted in each cell of the environment by its quantity and the percentage of infected mosquitoes. Other values were kept constant for each cell, namely, the number of eggs, the percentage of infected eggs and the level of water in that cell. These values were initialized uniformly for all executions and changed over time as the simulation progressed, based on neighborhood and presence of agents.

VI. EXPERIMENTS AND RESULTS

We perform in this paper all experiments described in our previous works [7] but this time using Lévy flights as randomization algorithm for the hybrid evolutionary agent model. We tested three different model combinations, namely, only with the genetic component enabled, only with the cultural component enabled and with both components enabled. This article proved the efficiency of the agent model with both components enabled through an social simulation with a real dengue fever spreading scenario. For this time, we build a Lévy flight module used by the agents. This section shows the comparison between the simulation with and without the Lévy flight module.

A. Experimental Setup

As the used agent model has two decision components (genetic and cultural) experiments were performed on both of these aspects.

The performance of each scenario was inferred by its approximation power relative to real data after 1 simulated year. The state of the population was inspected every 7 days. All simulations have two distinct stages, of which only the second is considered in results. The first stage is a free run

of 3 simulated months—a period of time needed to produce a more stable population behavior. After these three initial months, one year is simulated (second stage) and the results recorded.

To build a more realistic environment relative to public health services, 10% of population was induced to feel sick per iteration, generating extra demand for hospitals and health stations in addition to the regular infected agents demand—this idea captures the fact that in the real world, people get sick for other reasons that are not related to the spread of the Dengue fever. Each hospital or health station was allowed to set waiting queue limits and the total number of beds, which determines the number of agents that they are able to serve. In this work, we considered all simulated health units with waiting queue of size 50. The hospital of Iguaraci has 16 beds; the hospital of Afogados da Ingazeira has 96 beds; the hospital of Sertânia has 55 beds; each health station has only 1 bed.

Other parameters related to agent communication were as follows: global communication (i.e. the governmental broadcast mechanism used to instruct population on how to combat the dengue fever) reaches 60% of population per iteration; the instructed agent, called a “conscientious” agent, is capable of remove 5% of water of water pools in every location it visits; 1% of the population is initialized as conscientious. In local communication (i.e. communication between two agents) conscientious agents instructs others. The percentage of agents that an agent can locally communicate is determined by genetic factors.

The number of confirmed cases of dengue fever infection in the end of 2006 was 1. In the end of 2007, this number grows to 19. Thus, simulations were initialized with 1 infected agent in arbitrary dengue fever dissemination spots; another initialization factor is the concentration of mosquitoes and water pools in the town.

After one simulated year, we analyze the approximation power of each model configuration in a qualitative perspective and using quantitative real data. The analysis is focused basically on the percentage of sick individuals and the approximation of models to the real number, as well as the population behavior over time in a cultural and genetic perspective.

The genetic component has two parameters: the mutation and crossover rates. The mutation rate determines the probability of an agent to have its genetic code mutated per iteration, situation in which one of its genes is randomly modified. The crossover rate is the probability of an agent to crossover with another, generating a child agent. We have used a mutation rate of 0.5% and a crossover rate of 0.25%. This rates was obtained empirically comparing the real growth of population between 2006 and 2007.

All agents have a minimum and maximum initial lifetime set to be between 50 and 80 years—they are initialized randomly with values in this interval. Diseases have a negative effect on agents’ lifetimes . This models the fact that “natural” selection tends to prefer the dissemination of robust

genetic characteristics and cultural habits.

We compare 10 configurations combining components (genetic and cultural) with and without Lévy flight behavior. Simulations were carried out using an Intel R Core™ 2 Quad q 6600 64 bits 2.4GHz processor with 4GB of RAM. Results were averaged over 10 runs.

B. Simulation Results

We conducted two types of investigations for each scenario: (1) qualitative comparison of the model with real data; and (2) the influence of Lévy flight algorithm over the simulation. The first type of investigation was carried out through simulations parameterized with values from real data, with its qualitative results compared to real data after the simulation has finished. The second type of investigation was carried out through the observation of the simulation dynamics with the Lévy flight module. We compare 5 metrics with and without Lévy flight behavior.

Figure 4 shows the influence of Lévy flight on the number of infected agents over time. The overall number of infected agents reduces drastically. The Lévy flight behavior acts in the state transition dynamics causing agents to stay on the same state for longer than one iteration. This change prevents the agent to go to a place with a high concentration of infected mosquitoes. Real data tell us that, in the end of 2006, Iguaraci had a cumulative number of sick agents equal to 1, and in the end of 2007 equal to 19. Therefore, the best model, regarding quantitative terms is the one with cultural and genetic components an Lévy flight model enabled. This shows that the Lévy flight model provides a more realistic infection dynamic to the simulation than traditional random walk algorithms. Note that inertial behavior affected aspects related components, cultural and genetic, at same time during the simulation

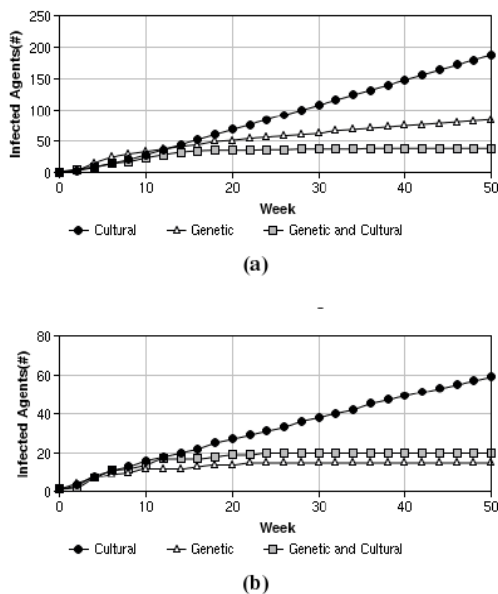


Fig. 4. Cumulative number of infected agents over time; (a) without Lévy flight, (b) with Lévy flight

Figure 5 shows that with Lévy flight the spread dengue is stopped earlier than the traditional randomization method. The better combination of components in Lévy flight simulation perspective is with both components enabled.

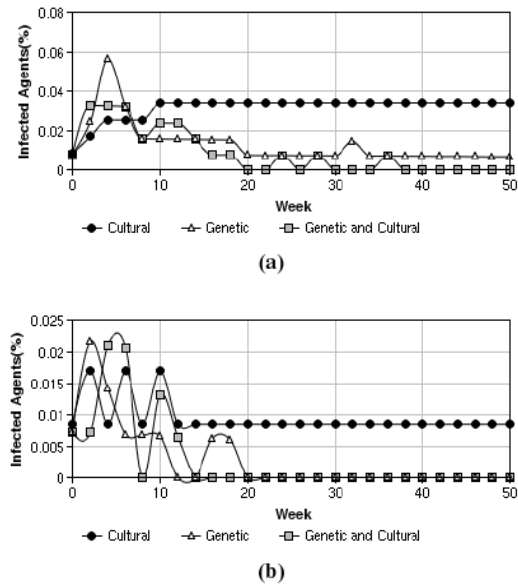
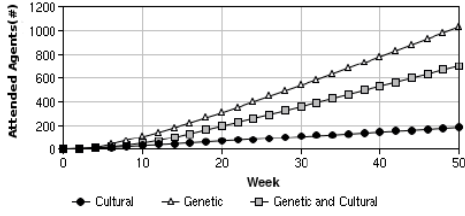


Fig. 5. Instantaneous percent of infected agents over time; (a) without lévy flight, (b) with lévy flight

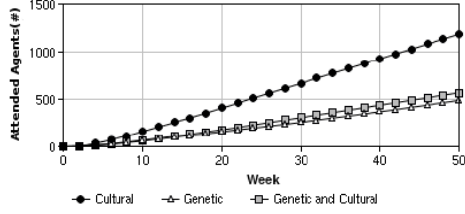
Figure 6 shows the comparison of the cumulative number of served agents in health units (hospitals and health stations) over time. These charts show interesting results between the Lévy flight and traditional randomization method. With Lévy flight randomization the number of served agents with only cultural component enabled increases rapidly compensating the high number of infected agents showed in the Figure 4. This pattern occurs because with Lévy flight randomization, the agent with only cultural component activated goes to the hospital in fewer iterations of the simulation. The cultural component is affected due its constant adaptation inside the agent’s “life”.

The inertial effect (provided by the Lévy flight algorithm) influences the formation dynamics of the cultural knowledge base. The interesting fact here is that the best result remains the one with both components activated, but the model with only the cultural component acts similar to the real data. The improvement on the cultural component helps the hybrid and evolutionary agent model to behave more realistically.

The number of served agents (in hospitals and health stations) is proportional to the number of infected agents with Lévy flight module enabled. Without Lévy flight, the sick agent delays to go to a health station or a hospital, walking inside the community without a fixed target. This sick agent can pass over health areas infecting others mosquitoes and agents. This is the cause of the proportional quantity of infected agents and attended agents using the Lévy flight module.



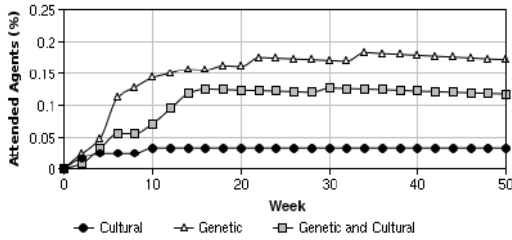
(a)



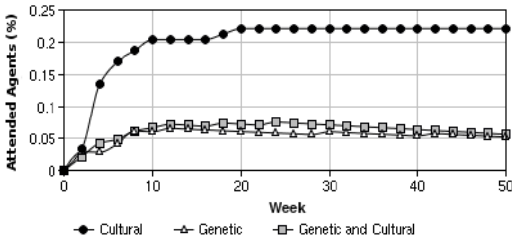
(b)

Fig. 6. Cumulative number of served agents over time; (a) without lévy flight, (b) with lévy flight

Figure 7 shows the percentage of served agents over time. This figure reinforces the influence of Lévy flight randomization method over the cultural component hypothesis. The number of served agents with only genetic component as well as with both components are small because there are less infections than with only cultural component.



(a)

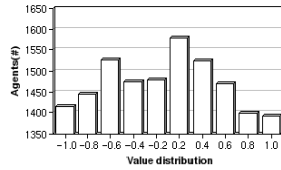


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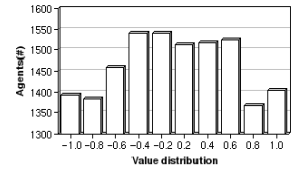
Fig. 7. Percent of served agents over time; (a) without lévy flight, (b) with lévy flight

Figures 8 and 9 show other interesting aspects observed in the Lévy flight simulation. The Gene 2 defines the agent tendency to stay in the current community and the Gene 3 defines the tendency to walk inside the community. We can observe the increase of agents that prefer stay inside

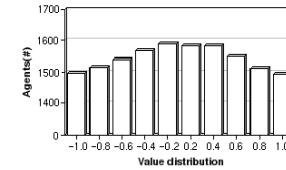
your community and do not like to walk (“lazy agents”) and agents that prefer to travel to meet others places (“travelers agent”). The genetic characteristics are more homogeneously distributed over the agents. This increases the agent diversity and perhaps is an indicator of a long term influence to the cultural component over the genetic component. This genetic configuration is obtained by the Lévy flight effect over the cultural component over the time. The genetic component is indirectly influenced by the Lévy flight randomization algorithm.



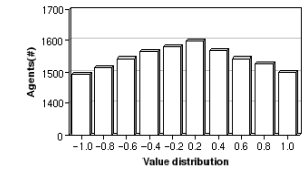
(a) Only genetic



(b) Genetic and Culture

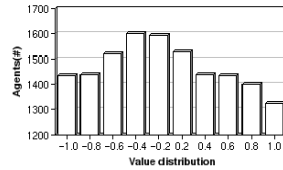


(c) Only Genetic

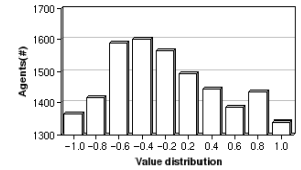


(d) Genetic and Culture

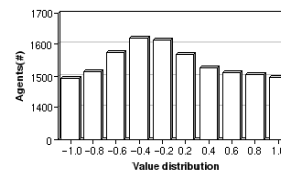
Fig. 8. Gene 2 distribution without Lévy flight randomization (a)(b) and with Lévy flight randomization (c)(d)



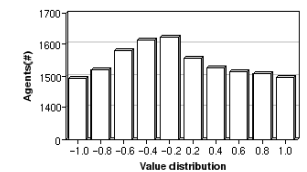
(a) Only genetic



(b) Genetic and Culture



(c) Only genetic



(d) Genetic and Culture

Fig. 9. Gene 3 distribution without Lévy flight randomization (a)(b) and with Lévy flight randomization (c)(d)

VII. CONCLUSIONS

For this article we provided a brief description of the Lévy probability distributions theory and its applications. We built a Lévy flight module for our hybrid and evolutionary agent model simulating a real-world scenario of the spread

of dengue fever in a small district of Pernambuco state, in Brazil.

The simulation was performed using the PAX Framework because it provides a flexible platform to build structures, environments and cognitive agent models.

The results showed us the relevance of use Lévy flight as randomization method for Agent-Based Simulation System. The cultural component is directly affected by the Lévy flight randomization helping the hybrid and evolutionary model to produce a more “human” behavior. This method produces plausible simulations improving the evolutionary and hybrid agent’s model.

Experiments results were compared quantitatively and qualitatively with the real data collected. We demonstrated the efficiency of Lévy flight as walk algorithm and state transition component for our hybrid and evolutionary agent model.

The put forward model can work as a general support decision tool for public-health officials. If appropriately set, it can test different configurations of scenarios determining which one is more favorable to solve the modeled problem (e.g. dengue fever spreading in the case of this paper). Using these simulations as a decision support tool, public officials may opt for solutions that yield more efficient results (economically and socially).

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