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Multi-agent geospatial simulation of human interactions and behaviour in bushfires

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ABSTRACT

Understanding human behaviour and interactions in risk situations may help to improve crisis management strategies in order to avoid the worst scenarios. In this paper we present a geospatial agent-based model and simulation of human behaviour in bushfires. We have modelled the social interactions between different actors involved in bushfires such as firefighter, police, emergency centre managers and civilians. We use the Belief, Desire and Intention (BDI) architecture to model realistic human behaviour, and the FIPA-ACL standard to model the communications. We use geospatial data to represent the environment in a realistic way. We show how the model has been implemented and how we have unified the communications model and the BDI architecture. Finally, we compare the processing time of two implementations of our model representing a 2D simple and a 3D GIS environment.

Keywords

Multi-agent systems, cognitive agents, GIS, communication, bushfires

INTRODUCTION

Between 1998 and 2017 climate-related and geophysical disasters killed 1.3 million people and left a further 4.4 billion injured, homeless, displaced or in need of emergency assistance (EM-DAT, 2017). Bushfires represent 3.5% of these disasters. Wildfires are uncontrolled fires which occur frequently in dry and hot climate zones. These fires devastate big forest areas, destroy properties and kill many people. In 7th February 2009, also called Black Saturday, bushfires killed 173 people in Australia in the state of Victoria. The Australian government created a commission in order to understand why so many people died despite its effort to prepare people for bushfire events. The conclusion of the commission (Rhodes, 2014) was that the responsibility was shared between all the actors involved: emergency managers, firefighters, police and civilians. In case of fire, the Australian Fire Authorities Council advise residents to choose between two courses of action: “Prepare, Stay and Defend” their house from fires, or “Prepare and Leave Early”. The emergency managers expected that civilians would follow instructions, prepare their fireplan and then apply it during the crisis. Despite the authorities’ expectations, many civilians did not have a fire plan or they applied it too late waiting for a personalised message from emergency centres.

Multi-agent modelling and simulation has proved to be a useful tool for exploring “what-if” scenarios, emergency management strategies (Almeida et al., 2013; Chu et al., 2009; Dugdale et al. 2010; Thorp et al., 2006) and communication strategies (Adam et al., 2019; Mancheva et al., 2015; Sakellariou et al., 2008) for a

better understanding of the human behaviour in crisis and emergency situations.

The focus of our work is to provide a realistic simulation of bushfires and people's behaviours and interactions. Our goal is to provide a tool for emergency managers and stakeholders to allow them to explore different strategies and scenarios. To achieve our goal we have used a combination of different research approaches including multi-agent simulation, cognitive modelling and geospatial information representation.

In this paper we present our conceptual agent-based model of human behaviour and interactions in bushfires and its implementation. In the first section, we describe the state of the art concerning the research areas involved in our model. Then, we describe the theoretical foundations of our model and how it was constructed. We then show how this model was implemented and compare a 2D simple model and 3D GIS model in terms of processing time. We conclude with a summary and discussion about the model and our contributions.

STATE OF THE ART

We use an agent based modelling (ABM) approach to model and simulate human behaviour, and geographic information system (GIS) data to provide a more realistic environment.

ABM had been widely used for modelling and simulating human behaviour in different natural hazard situations such as earthquakes (Bangate et al., 2017), floods (Dawson et al., 2011), tsunamis (Mas et al., 2012) and bushfires (Adam et al., 2016; Minelli & Tonini, 2016; Thorp et al., 2006). ABM can capture emergent phenomena in complex systems, provide a natural description of such a system, and is flexible enough to model the micro and macro levels in a system (Bonabeau, 2002). Agents are defined by the following characteristics: (1) autonomy: each agent can control its own actions and its internal state; (2) heterogeneity: each agent can have its own specific set of attributes and behaviours; (3) social ability: agents can interact with each other via some kind of agent communication language (ACL); (4) bounded rationality: agents' knowledge is not universal but depends on their context; (5) reactivity: agents can perceive their environment (physical or abstract) and respond to the changes in it; (6) proactiveness: agents do not only perceive and act in their environment but exhibit goal-directed behavior (Wooldridge & Jennings, 1995; Crooks et al., 2018). These agents' characteristics show that ABM is an appropriate tool to model a complex system such as bushfires where different actors with heterogeneous behaviours interact with each other. Another way to model complex systems is to use equation based models. The advantage of using ABM instead of mathematical equations is that ABM can model entities with heterogeneous behaviour often with nonlinear relationships and with multiple interactions. For a complete discussion about ABM vs equation-based modelling see (Parunak et al. 1999).

There are several ways to model human behaviour in ABM, the simplest one is to use reactive agents whose behaviour is based on a perception - action loop. A more realistic and sophisticated approach is to use the BDI (*Belief, Desire, Intention*) (Rao & Georgeff, 1991) cognitive model. This model is based on Michael Bratman's philosophical theory of action (Bratman, 1987). Human behaviour is described in terms of mental attitudes: *Beliefs, Desires and Intentions*. The *Beliefs* represent the knowledge that the agent has about the world (not necessarily true); the *Desires* represent the actions that agent would like to do in the future; and the *Intentions* are the chosen actions that will allow the agent to accomplish its goals. It is possible that the agent has different plans to achieve the same *Intention*. In this case, if one of the plans fails, another one will be selected. For (Adam et al., 2016), BDI is a more appropriate approach for modelling human behaviour in crisis situations involving complex decision making, influenced by emotions and by the social context than reactive agents.

Another important issue that should be considered when modelling human behaviour in emergency situations, is communication. Modelling communications allows us to implement a realistic spread of the information between different actors. Communication is a social interaction and can be viewed as a complex system where entities, e.g. humans, interact using a common language. Different standards for Agents Communication Language (ACL) exist, we have chosen to use FIPA (Foundation for Intelligent Physical Agents) - ACL (Fipa, A.C.L., 2002) that is widely adopted in ABM. Based on its theoretical foundations FIPA-ACL can be easily integrated into a BDI agent architecture. For example, (Mancheva et al., 2015) used FIPA and BDI to model the communications in a medical team during cardiopulmonary resuscitation. In ABM of bushfires (Sakellariou et al., 2008) used FIPA-ACL and BDI to model firefighters cooperation for extinguishing forest fires. Also (Adam et al., 2019) used BDI agents and created their own framework for agent's communication in order to study the best ways for information spreading concerning bushfires.

(Wise, 2014) argues that combining GIS and ABM allows researchers to gain better insight into how a crisis may develop and to explore how boundedly rational individuals behave in a complex physical environment. There are several examples of models combining GIS and ABM, for a complete review see (Crooks et al., 2018). Here we are interested in how ABM and GIS have been used in bushfires. (Minelli & Tonini, 2016) designed an ABM that simulated alpine forest fires, urban traffic and firefighters using GIS data. (Thorp et al.,

2006) also used ABM and GIS to model wildfires, traffic simulation and evacuation in Santa Fe, USA. Although these models provide good frameworks to study fire spreading, traffic simulation and evacuation in a geospatial environment, they do not provide any fine grained behaviour model of different actors in such a situation. On the contrary (Adam et al., 2016; Adam et al., 2017) created a detailed cognitive model of civilian behaviour in bushfires and simulated it using ABM, but they did not use GIS data.

This paper describes a unified framework for simulating realistic crisis situation scenarios. To our knowledge, there is no research study that has simultaneously employed detailed cognitive modelling of different actors in bushfire situations, using an advanced language for communication based on speech act theory, and integrating spatio-temporal information.

CONCEPTUAL MODEL

The model is inspired by a body of work modelling the human behaviour in bushfires (Adam et al., 2016; Adam et al. 2017; Adam et al. 2019). The model has been designed based on the data from witness statements (Exell, 2009) of people who survived the 2009 Black Saturday fires in Victoria, Australia. These witness statements provide realistic data of how civilians responded to bushfires. We have manually analysed the 100 witnesses' interviews to help to construct the model, and also used statistics about the victims (Teague et al., 2009), for example:

- Causes of death: 14% died while escaping (4% by car and 10 % by foot); 69% died while passively sheltering in a building; 17% died trying to defend their house.
- Preparation: 58% of victims had made no preparation to their property or themselves; 20% intended to stay and defend their property and were well prepared.
- Awareness: of those who died, 30% were taken by surprise, 38% did not have any knowledge about what to do.

System Specification

The architecture of the model is shown in Figure 1. For the sake of readability, we have removed all attributes and methods of simple reactive agents and have kept only BDI agents definitions. We have defined 3 abstract types of agents: *WeatherAgents*, *LandAgents* and *GameAgents*.

Weather agents

Fire

Since the focus of our work is on modelling human behaviour in bushfires, we did not use a complex fire spreading model, as done in other studies (Duff et al., 2013). The fire starts at a random time (measured in simulation cycles), and location at the beginning of the simulation; simultaneous fires are also possible. Fire has different attributes such as damage radius, heat radius and intensity. The intensity is the fire strength of damaging buildings within a damage radius. The heat radius represents the radiant heat around the fire that injures civilians. At each simulation step, based on a probability, the fire can grow by increasing its intensity, propagate in a radius, emit embers, injure civilians and damage buildings. It can also stop burning when extinguished by firefighters, by modifying its intensity to null.

Forecast

The Forecast agent has the role of observing fires and displaying different fire danger ratings as a function of the number of fires and their intensity. The ratings include: low, high and severe state. Different agents (e.g. civilian, emergency managers) can check the Forecast agent's danger ratings at any time.

LandAgents

LandAgents include all landscape agents: roads, buildings, water areas and forests. The *LandAgents* are created from real geospatial data. The processing of the GIS data is explained in the Implementation section. The number, location and shape of roads, water areas, forests and buildings depend on this data.

Roads

The roads are represented by a graph. This road network is used by agents (e.g. civilian, police and firefighters) driving a car or a truck. A road could be blocked by a fire or by the police. In future versions, we would like to

calculate a speed coefficient (as a function of the road capacity and width) that will decrease the speed of driving agents, simulating traffic jams.

Water Area

Water areas are used for recharging fire truck water containers. Since the available quantity of water in these areas is huge, we simplify and consider it to be unlimited for now. In the future versions, water areas can be used as shelters for civilians, as noted in witness statements.

Forest

The forest has attributes describing its density, dryness and height.

Obstacles

The obstacles are an abstract class of agents that gathers all non-human agents that could block the movement of human agents (e.g. civilian, firefighter and police). We have implemented a mechanism so that agents avoid buildings and fires.

Building

Three types of buildings are modelled: house, shelter and base (for police or firefighter agents). All buildings have a fire resistance level. For shelters and bases this resistance is set to maximum, they cannot be destroyed. Agents inside shelters and bases cannot be injured by the fire. A house can have zero or one occupant. This choice was done for model simplicity, since including family interactions can significantly increase the model complexity. Houses have some initial resistance that can be increased if the owner decides to prepare it (e.g. remove fuels and garden furniture, put sprinklers on). When the resistance drops to 0, the house collapses (shown in black in the simulation view). If the owner is in or close to the house, the collapse will remove his plans to shelter in the house or to defend it.

GameAgents

GameAgents have common characteristics like speed, perception radius (auditory and visual), list of fires, and ability to communicate. The agent's speed depends on the agent's mean of transport (e.g. by car/fire truck or by foot). The perception radius represents the area around the agent where it can "see" and "hear" other agents (e.g. civilians, fire, buildings, etc.). The list of fires contains the perceived fires by the agent in its perception radius. Note that, even if some of the fires are extinguished, the agent will continue to believe that a fire exists at a certain location until it perceives that there is no longer a fire at that location. All GameAgents are implemented with a BDI architecture.

Helicopters

Helicopters search for fires and report their coordinates to emergency managers. For simplicity's sake, the helicopter agents are basic and do not extinguish fires. At the beginning of the simulation helicopters are located at their base and once they receive an order from an authority agent, they start to search for fires. If they perceive a new fire in their perception radius, they will report its location to the authority agent. Helicopters continue to search for fires until the end of the simulation, when all fires stop.

Police

According to the witness statements, the Australian police has the role of informing people and blocking roads to prevent citizens from moving towards a fire. At the beginning of the simulation, police agents are located in their base. They can go to a specific road location when requested to do so by the authority agent, moving only by car on the road network. The police agents can inform the authority agent about newly perceived fires, or inform civilians about further fires on the road.

Authority

To simplify, we have decided to model the emergency manager's behaviour and the authority's behaviour into one single abstract agent that we call Authority. The Authority agent has two main goals: extinguish fires and save residents. At the beginning of the simulation, the Authority agent observes the forecast provided by the Forecast agent. If the fire danger level is high, it can decide to achieve its goals with plans among the following:

- Get global information about the fire location: by requesting helicopters to fly over specific areas
- Get local information about fire location: by requesting the police to go to strategic road network hubs
- Deploy firefighters trucks to fire locations: by managing busy or available firefighters and active fires locations
- Broadcast emergency evacuation alert to civilians

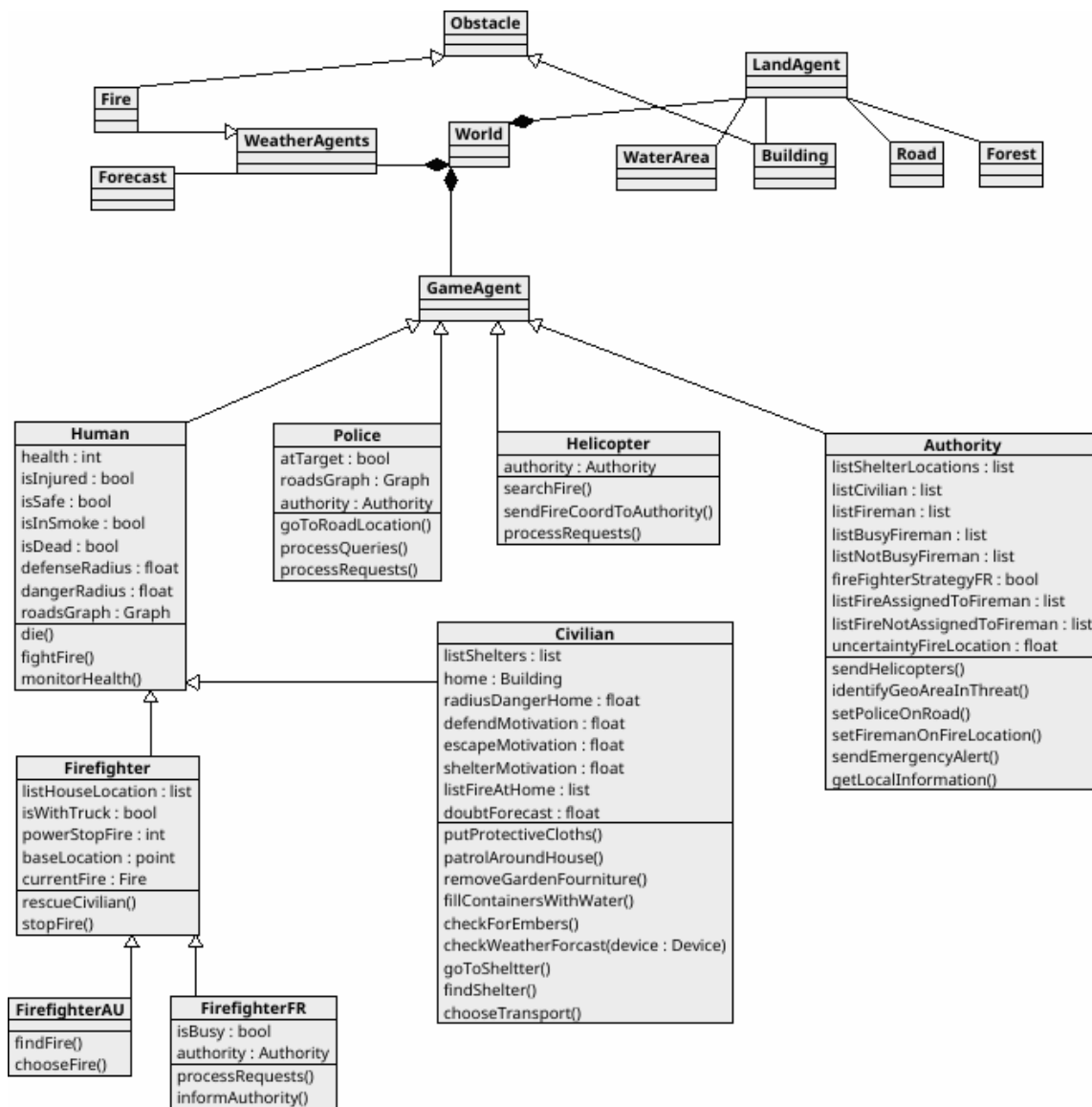


Figure 1. Simplified UML class diagram of the model

Firefighter

In our model the firefighters have 2 main goals: extinguish fires and save civilians. The firefighter's priority is always to save people's lives even if there is a nearby intense fire¹. In the introduction we stated our goal of providing a tool for testing emergency management strategies. Firefighters in different countries have different protocols and strategies when they extinguish fires. We have decided to model and implement both the Australian and French firefighter's strategies. From interviews, we know that Australian firefighters work in a decentralized manner, going from one fire to another. Conversely, French firefighter management is more centralized. French firefighters are given orders to go and extinguish a fire at a specific location and when the fire is under control, they go back to their base and wait for new orders. Depending on a boolean parameter, the firefighters in our simulation apply either the Australian or French strategy. In both cases at the start of the simulation, the firefighters are located at their base. French firefighters receive orders from the Authority agent to go to a specific location and extinguish a fire. Once the fire is stopped they go back to their base and inform the authority that they are available and that the fire on that location is stopped. Australian firefighters listen to the forecast and when they believe that there is fire danger, they start to search for fires. When they stop a fire, they search for another one. Firefighters move on the road network driving fire trucks at a random speed. The fire truck has limited water capacity and when the water is used, firefighters refill with water at the closest water area. At any time during the simulation, if firefighters perceive an injured civilian, they will put on hold all other

¹ Source: private communication with French firefighter, requesting anonymity.

plans and will attend to the injured civilian. Once the civilian has been attended to, it is removed from the simulation; this represents the idea that the civilian has been driven to hospital or a safe area.

Civilian

Our model uses data of civilians that survived the Australian bushfires. Residents have to choose between two fire plans: “Prepare, Stay and Defend” or “Prepare and Leave Early”². In our model, civilians can either defend their house, leave it or passively shelter in the house depending on a motivation parameter. At the beginning of the simulation, civilians are located in their houses or they move (by car or by foot) around their environment. There are 2 ways for a civilian to believe that there is fire danger: either they perceive a fire in their perception radius or they receive an evacuation alert from the Authority agent. If a civilian knows that there is fire danger, he will activate his fire plan to stay, to go or to passively shelter in his house. Civilians can escape by foot or by car depending on a probability parameter, set from the statistics shown in the beginning of this section. Civilians can go to a shelter selected among their known shelters list. If the civilian decides to defend his property, he can choose first to prepare his property and/or himself. To defend his property, the civilian goes around his house within a protection radius and searches for fires and embers. Beyond a danger threshold based on the number of fires around his house, the civilian may decide to shelter inside until the end of the simulation or go to a shelter.

Communication model

We model agent’s communications with FIPA-ACL (Fipa, 2002). FIPA-ACL is based on speech act theory (Searle, 1969) that considers an utterance as having a performative function in language and communication. Based on that theory, exchanging information (receiving/sending a message) is an action in our model. A FIPA message has several parameters; we have simplified the message structure as follows: type, sender, receiver and content. FIPA specification defines 22 communicative acts. From witness statements and based on our agent BDI model’s constraints, we have chosen to use the following 3 acts:

- **inform-ref:** the sender informs the receiver for an object description.
- **query-ref:** ask another agent for a referred object value (e.g. fire location).
- **request:** the sender requests the receiver to perform some action (e.g. go to fire location).

Here are some examples of messages exchanged between two agents in our model:

request (authority, police, [GO_TO: {125; 456; 852}]): the authority agent requests a police agent to go to road location with coordinates {125; 456; 852}

inform-ref (helicopter, authority, [FIRE_LOCATION: {863; 15; 335}]): the helicopter agent informs the authority about a fire perceived at coordinates {863; 15; 335}

query-ref (authority, police, [FIRE_LOCATION]): the authority agent queries the police if the police knows of a new fire location

We will demonstrate in the next section how we have implemented these specifications into the agent’s BDI model.

Dynamic model

We have used the Tactics Development Framework (TDF) to design the dynamic specifications (Evertsz et al., 2014) of all cognitive agents in our simulation. This methodology has already been used for crisis situations and has proven its utility in other studies modelling human behaviour in bushfires (Adam et al., 2016). The TDF methodology is composed of 3 phases: (1) *System specification*: definition of goals, scenarios, percepts, actions, data, actors and roles; (2) *Architectural design*: specification of agent’s interactions (via protocols) and messages; (3) *Detailed design*: detailed agent plan diagrams including subgoals, internal messages and actions. Here we will describe the architectural design and the detailed design of our model.

Architectural design

In the architectural design we have specified all agent interactions that can occur during the simulation. Figure 2 shows a detailed view of all possible messages between different agents as well as their contents. We have used the formalism defined in the previous section. Each colored square in Figure 2 represents the communications for a specific agent and the directed arrows - the receiver agent. For example we can see that the Civilian agent can send messages to the Authority agent, the police, the firefighters and to the other civilians.

² Hereafter referred as ‘stay’ or ‘go’ plan

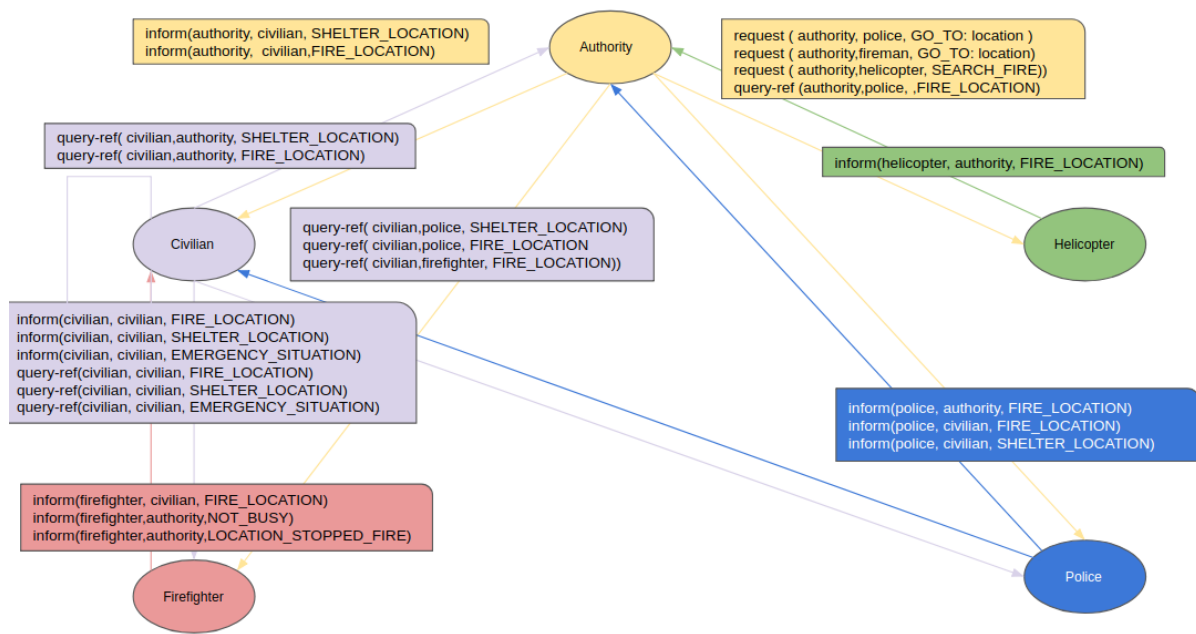


Figure 2. Architectural design: specification of agents' interactions

Detailed design

The detailed diagrams are very useful for the modeller since they allow making a direct link between the agent's goals and its BDI specifications and implementation. Due to space limitations we will only show a detailed diagram of authority agent goals.

Authority

Figure 3 details the authority subgoals and plans of the Stop Fire goal. The Stop Fire goal is activated when the authority agent believes that there is fire danger provided by Forecast agent. To stop the fire the authority agent has to know where the fire is and then deploy firefighters to that location. The authority agent can also deploy police agents at strategic road locations in order to inform residents. We split the Stop Fire goal into 2 sub-goals Get fire information and Set emergency service on road. Get fire information goal is achieved by applying 2 plans Get global information and Get local information. Get local information is executed under certain conditions: police have to be already deployed on the road network, and the authority's uncertainty level about the fire location should exceed a fixed threshold. This threshold increases with each simulation step and decreases when the authority agent receives fire location information. Using the threshold condition means that we can model in a realistic way several calls of Get local information plan. This plan consists of one action, the authority queries the police if it knows about new fire locations. As we explained in the previous section, we consider a communication as an action. As in real life, when an emergency manager is uncertain about the fire location, he will call the services located on-site. Set emergency service on road is split into 2 plans: Deploy firefighter on road and Deploy police on road. The Deploy firefighter on road plan will be called only if the authority is managing French firefighters and if the list of active fires is not empty. In this case, the authority agent has to optimise the deployment of firefighters resources to specific fire locations.

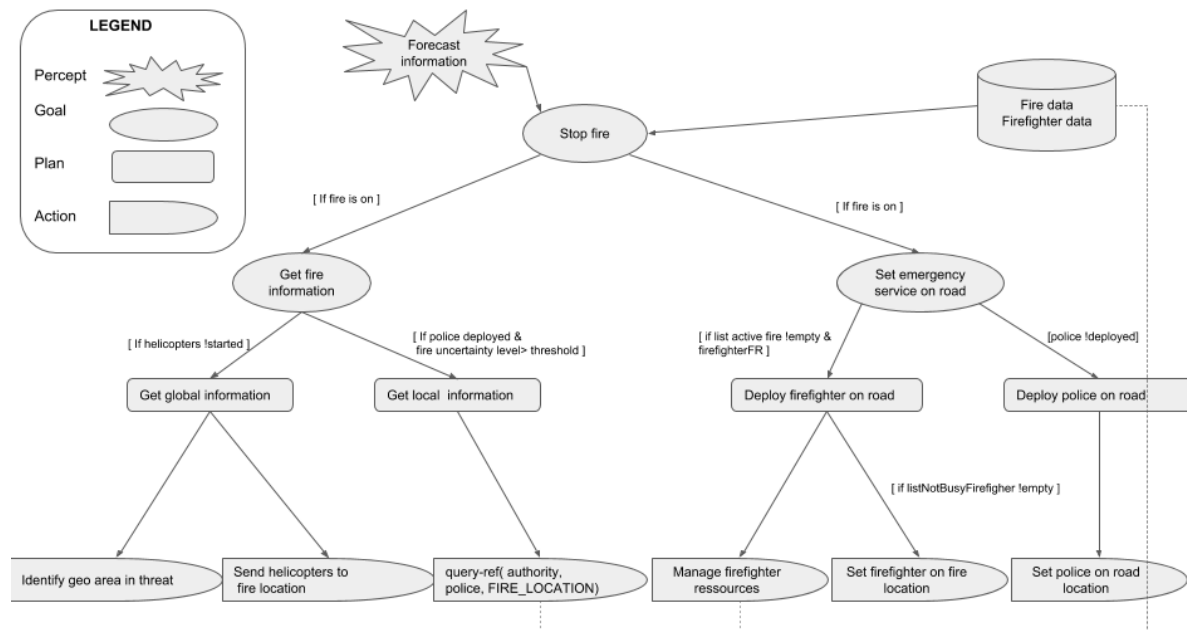


Figure 3 . Detailed design: Diagram of authority agent Stop fire goal.

IMPLEMENTATION OF THE MODEL

Many agent based simulation platforms exist; for a review and comparison see (Kravari & Bassiliades, 2015). We have used the GAMA platform (Grignard et al., 2013) for implementing our model. GAMA is an open source modelling and simulation development environment for building spatial agent-based simulations. GAMA uses a meta agent oriented programming language called GAML. GAMA combines GIS data and 2D/3D visualisation and supports the implementation of large scale models. It also includes a BDI plugin that allows modellers to easily implement BDI agents, and it is FIPA-compliant. All these characteristics fit very well with the requirements of our model.

Agent's world

The agent's world can be built in 1 of 2 different alternative ways: (1) 2D model; (2) 3D GIS model. All agents in our model are world-agnostic, meaning that they have a generic implementation independent of the world's specifications. This allows us to use different environment visualisations, setups and different maps. At the beginning of the simulation, in the GUI view, we can select between the 2 different models.

2D model

The 2D model has simpler view and smaller dimensions than the real 3D geospatial model, allowing us to see small agents without zooming (e.g. civilian are 2m high). Figure 4 is a 2D model screenshot. All agents are generated at random locations. The map represents roads graph network, painted in pink. We can see small fires close to some houses and civilians 'defending' them. On the bottom right side, firefighters are leaving their base (green square) and driving towards fires.

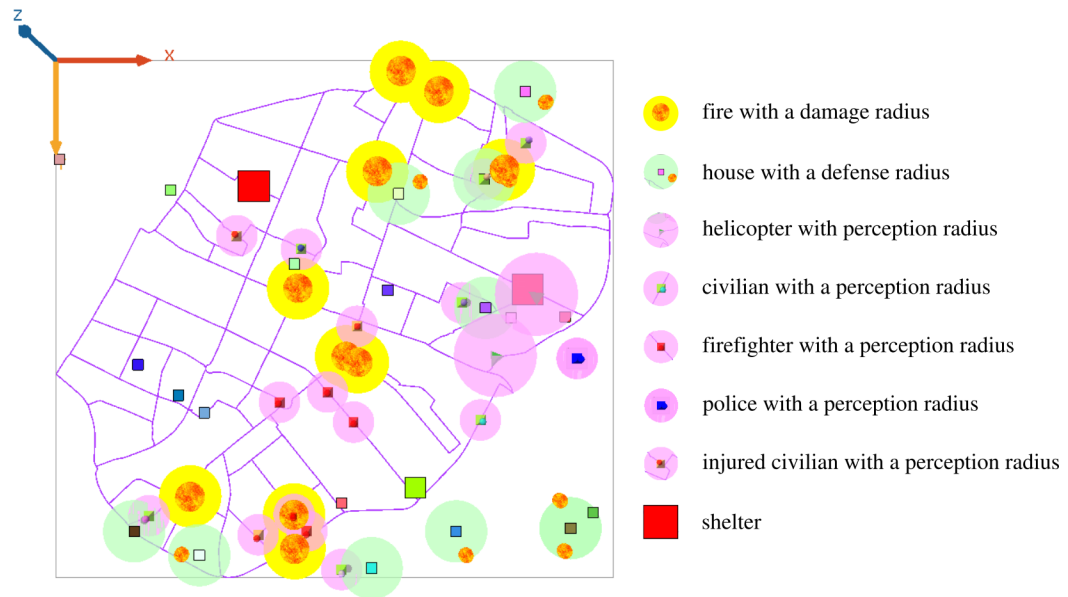


Figure 4. 2D model screenshot at cycle 17 since the beginning of the simulation

3D geospatial model

GIS data can be easily integrated into the agent model by providing shapefiles³ that specify different geographical objects. Non-human agents, such as forests, buildings, roads and water areas, are created from these shapefiles. We have used OpenStreetMap⁴ for obtaining GIS data and then GAMA to process and save them into shapefiles. We used also QGIS⁵ to change the shapefiles spatial reference system to the corresponding Australian one, GDA94⁶. We model the Kinglake city area, in Victoria, because it was one of the most affected cities during Black Saturday. Figure 5 shows a screenshot of the simulation using the GIS data of Kinglake city; we can see the same agents and colours but with a different layout. Although buildings, fires and road network are visible, we cannot see civilians, firefighters and police since their size is too small at this scale. The green area represents the forest.

BDI implementation

GAMA provides a BDI plugin (Taillandier et al, 2016) to create BDI agents with the GAML language. A BDI agent has a plan library and 3 different databases for beliefs, desires and intentions. An engine updates these based on the agent's perceptions of its environment and its internal rules. In GAML, a specific type called predicate is used to describe the domain ontology. Here is a code snippet giving an example of predicate definition.

```
predicate get_local_info_fire <- new_predicate ("get local info fire");
predicate set_emergency_service_police <- new_predicate ("set emergency service police");
```

Below is an example of an authority agent rule that generates the desire to get local information about fires only when it believes that the police are deployed on the road and when its uncertainty level exceeds a threshold. This example shows part of the implementation of the conceptual model described in Figure 3.

³ A shapefile is a widely used geospatial vector data format for GIS.

⁴ OpenStreetMap is a free editable map of the world, created by volunteers, <https://www.openstreetmap.org>

⁵ QGIS is an open-source platform for GIS data processing.

⁶ GDA94 is Geocentric Datum of Australia 1994

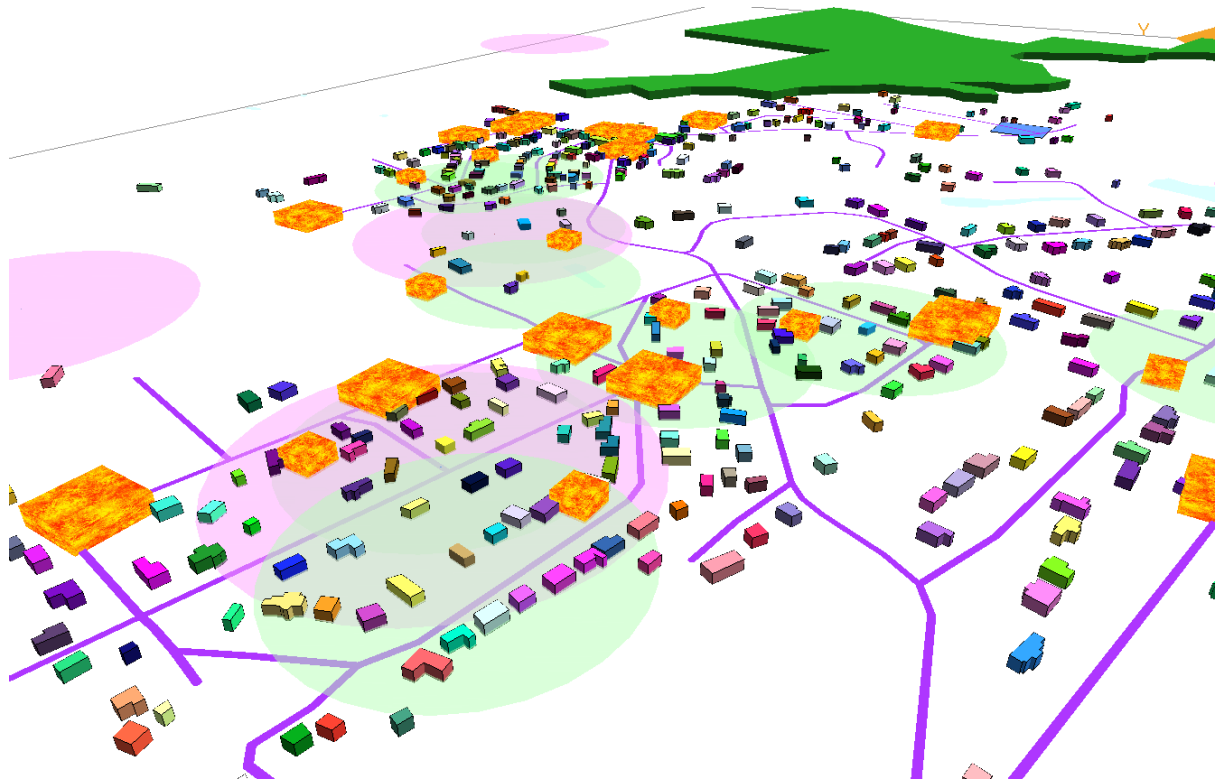


Figure 5. 3D model screenshot of Kinglake city in Victoria state, Australia, representing 4000m x 3000m map

```
rule when: has_belief(set_emergency_service_police) and uncertainLocationFire > 0.7 new_desire:
get_local_info_fire ;
```

BDI agents also have a library of plans for achieving their intentions. For instance, the following plan accomplishes the `get_local_info_fire` intention by calling the action `queryPolice`.

```
plan getLocalInfoFire intention: get_local_info_fire {
  do queryPolice;
}
```

In that action, the authority agent queries each Police agent, one by one about the fire location. Since, it knows that it will receive the fire location information, the uncertainty threshold decreases to 0, so the next simulation step the rule presented earlier won't be executed. Adding the belief of getting the local information will remove the `get_local_info_fire` intention from the intention stack.

```
action queryPolice {
  loop p over:list (Police) {
do_start_conversation to: [p] protocol: 'no-protocol' performative: 'query' contents: [ (
FIRE_LOCATION )];
  }
  uncertainLocationFire <- 0.0;
  do_add_belief(get_local_info_fire); }
```

FIPA implementation

In GAMA, if an agent is specified with a FIPA capability, it is provided with embedded actions and lists that hold different FIPA communicative acts and communications. Below are GAMA examples of the speech acts that we model:

```
do start_conversation to: [a] protocol: 'no-protocol' performative: 'inform' contents: [ ( msg ) ];
do start_conversation to: [a] protocol: 'no-protocol' performative: 'query' contents: [ ( msg ) ];
do start_conversation to: [a] protocol: 'no-protocol' performative: 'request' contents: [ ( msg ) ];
```

In the action queryPolice, the authority agent individually queries police agents about the fire location. GAMA also provides default lists for receiving different messages: informs, queries and requests lists. However, the modeller has to specify the message processing in different lists. Here is a code snippet of agent reflex⁷ reading its list of informs messages:

```
reflex readInforms when:!empty(informs) {
    loop i over: informs {
        string msgContent <- string(i.contents);
    ..... }
}
```

PRELIMINARY RESULTS

Below are some preliminary results. We have compared the processing time (in minutes) between the 2 models with different scenarios (Table 1). We ran 5 simulations per scenario, varying just one parameter at a time; the remaining parameters did not vary between simulations. We have chosen to stop the simulation at 500 cycles in order to avoid waiting until all fires have been extinguished. We examined how the number of BDI agents and reactive agents affect the model performance for both the 2D and 3D model. We have chosen Civilian agents to represent BDI agents and Fire agents to represent the reactive agents in the model comparison.

Table 1. Simulation Experiments

	2D model	3D model
Scenario 1	20 Civilians & 5 Fires	20 Civilians & 5 Fires
Scenario 2	100 Civilians & 5 Fires	100 Civilians & 5 Fires
Scenario 3	20 Civilians & 100 Fires	20 Civilians & 100 Fires

Figure 6 shows the probability density function of the simulation duration for the different scenarios in Table 1. We verified the effect of increasing the number of reactive agents (from 5 Fires to 100 Fires) by comparing the processing times in 2D model Scenario 1 (the green bell on Figure 6) and Scenario 3 (ocher bell) (t-test p-value = 0.26 > 0.05) as well as in the 3D model Scenario 1 (pink bell) and Scenario 3 (blue bell) (t-test p-value = 0.21 > 0.05). We can see from t-test results, that that is no significant difference in processing times for 2D and 3D models when we increase the number of reactive agents (Fires). We have then verified the effect of increasing the number of BDI agents (from 20 civilian to 100 civilian) by comparing the Scenario 1 (green bell for 2D; pink for 3D) and Scenario 2 (orange bell for 2D; cyan for 3D) and we found that there is significant difference in the processing times (2D model t-test p-value = 0.00003 < 0.05; 3D model t-test p-value = 0.0002 < 0.05). We have compared Scenario 1, 2, 3 for 2D and 3D model, and we have found a significant difference in processing times between both models, indicating that GIS data display and processing is time consuming.

⁷ A method that is called each simulation step

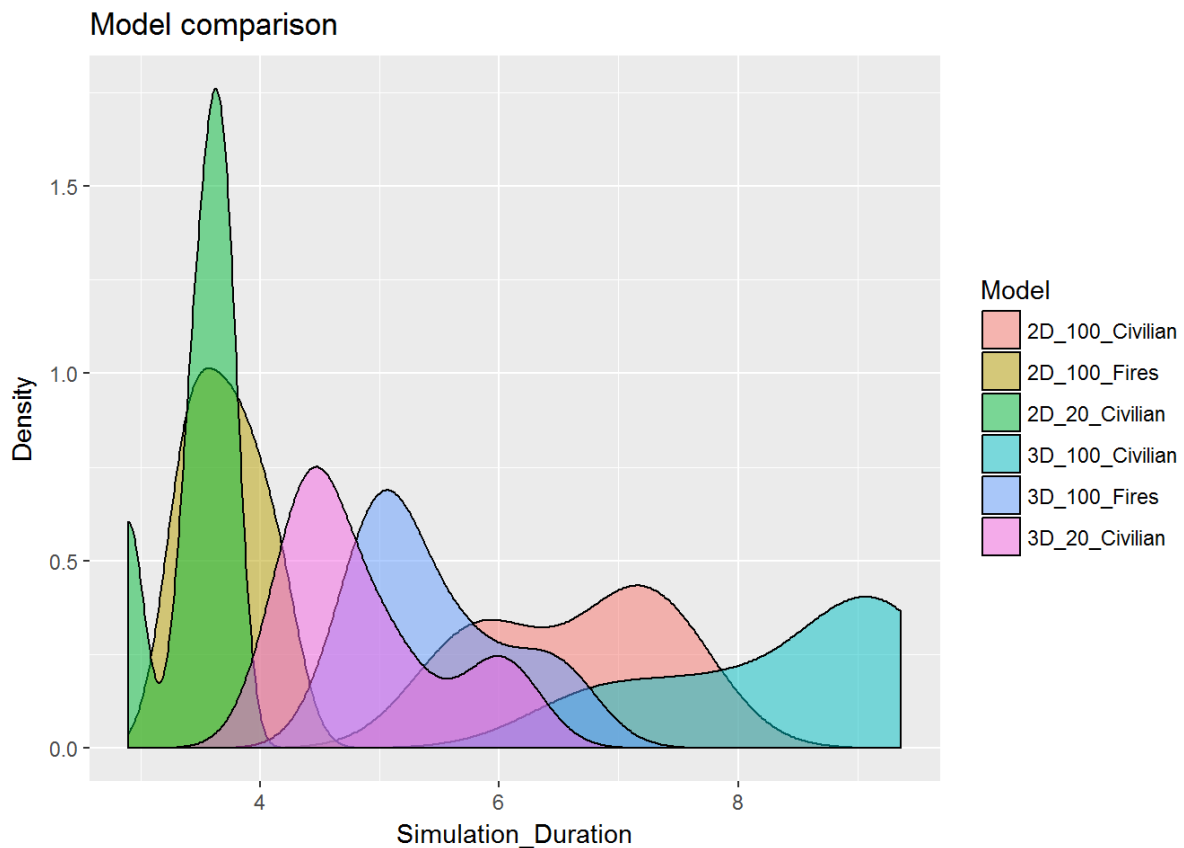


Figure 6. Comparison of the 2D and 3D model processing time (in minutes)

CONCLUSION

The goal of our work was to present a unified framework for modelling a complex crisis situation such as the human behaviours and interactions in bushfires. We proposed agent-based model including BDI cognitive modelling combined with the FIPA standard for communications, and a GIS for modelling a realistic environment which to our knowledge has not yet been done before. We described how we built our conceptual model using UML and TDF and how the model was implemented using the GAMA agent-based platform. We also demonstrated the flexibility of our model showing that the same agents' implementation can be represented in a 2D simple model or a 3D GIS model. The preliminary results showed that a 3D GIS model takes significantly more processing time than the 2D simplified model and that increasing the number of BDI agents also significantly affects the processing time. This constrains the modeller to make a fair trade off between the model complexity and realism in the agent's design. In this paper, we have presented the first preliminary results and in the future work we need to do internal and external validation of the model.

In future work, we will explore the model's parameters space and perform a sensitivity analysis. The model will then be validated by comparing the model's results to the statistical observations reported by (Teague et al., 2009). Once the model is validated, we would like to examine different scenarios. For example, to assess the Australian and French firefighter strategies in different fire configurations (e.g. concentration of the fire at one location/more locations and in function of the distance between fires) in order to determine which strategy is more appropriated to which scenario. We can also test different emergency manager strategies for the management of the available firefighters (e.g. is it better to extinguish first fires with big fire spread or with big intensity?) or for the police locations (at which road location, the police will inform more civilian about the fire situation). This realistic model will allow emergency managers and stakeholders to get valid results transferable to real life situations. We then wish to modify the model into a serious game for emergency situation training.

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