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Análisis de la intervención policial en las paradas cardiacas extra-hospitalarias utilizando modelos de simulación basados en agentes

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Analysis of police intervention in out-of-hospital cardiac arrests using agent-based simulation models.

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Que el trabajo titulado ‘’Análisis de la intervención policial en las paradas cardiacas extra-hospitalarias utilizando modelos de simulación basados en agentes’’, que se presenta, ha sido realizado por Miguel Baigorri Iguzquiaguirre, con DNI número ***23705Ty constituye la memoria del trabajo realizado para la superación de la asignatura Trabajo Fin de Máster del Máster Universitario en Modelización Matemática de la Universidad de Salamanca

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Resumen

En este trabajo se analiza el impacto en la supervivencia de pacientes que tiene dotar a la policía local con Desfibriladores Externos Automáticos (DEA) para atender paradas cardiacas extra-hospitalarias (OHCAs). Para ello se desarrolla un modelo de simulación innovador, que combina simulación basada en agentes con simulación de eventos discretos. Cada agente viene descrito por su motivación, que afecta a su disposición a atender sesiones de entrenamiento; su tasa de aprendizaje y su nivel de entrenamiento. Cada agente es único y sus atributos cambian en el tiempo dependiendo de los resultados de las OHCAs que atiende, y, al mismo tiempo, el resultado de la OHCA depende del nivel de entrenamiento del agente que realiza la reanimación. El modelo permite evaluar la mejora en la probabilidad de supervivencia a una OHCA cuando la policía municipal participa como primer interviniente, además de los servicios de urgencia extra-hospitalarios y de los ciudadanos que tienen a su disposición la red pública de desfibriladores, bajo distintos escenarios formativos y de patrullaje para la policía. En la construcción del modelo matemático se utilizan resultados sobre la influencia del nivel de entrenamiento en el resultado de las paradas cardiacas y sobre procesos de aprendizaje y olvido de habilidades de uso poco frecuente expuestos en literatura médica que no habían sido considerados previamente en el modelado matemático de agentes.

Palabras clave

Modelado Matemático, Simulación basada en Agentes, Simulación de Eventos Discretos, Parada Cardio-Respiratoria Extra-Hospitalaria, Desfribilador Externo Automatico, .

Abstract

This paper focuses on analyzing the impact of equipping local police with Automated External Defibrillators (AEDs) to attend out-of-hospital cardiac arrests. (OHCAs). To do so an innovative simulation model is developed, which combines agent-based and discrete event simulation. Each police officer is described by its motivation, which affects its willingness to attend training lessons, its learning rate and its training level. Each officer is unique, and its attributes change depending on the outcome of the OHCAs the officer has attended, while at the same time this outcome is affected by the training level of the officer. The outcome of the OHCAs is measured in terms of survival probability of the patient, which is considered a function of the time of the first response and the training level of the first responder. The model allows to evaluate the improvement in the probability of survival of an OHCA when the local police participate as first responders, in addition to out-of-hospital emergency services and citizens who have at their disposal the public defibrillator network, under different training and patrolling scenarios for the police. The construction of the mathematical model uses results on the influence of training level on the outcome of cardiac arrest and on learning and forgetting processes of infrequently used skills reported in the medical literature that had not previously been considered in the mathematical modeling of agents.

Key Words

Mathematical modelling, Agent Based Simulation (ABS), Discrete Event Simulation (DES), Out-of-hospital cardiac arrests (OHCAs), Automated External Defribillators (AEDs), .

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List of Abbreviations

OHCA: Out-of-Hospital Cardiac Arrest

AED: Automated External Defibrillator

CPR: Cardiopulmonary Resuscitation

DES: Discrete Event Simulation

ABS: Agent-Based Simulation

ABMS: Agent-Based Modelling and Simulation

SD: System Dynamics

OSM: Open Street Maps

AHA: American Heart Association

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Introduction

This project develops an original model to study the impact of equipping Automated External Defibrillators (AEDs) in local police cars and training police agents in Cardiopulmonary Resuscitation (CPR) and defibrillation on the patient's survival probability to an Out-of-Hospital Cardiac Arrest (OHCA) event. The proposed model combines the Discrete Events Simulation (DES) paradigm with the Agent Based Simulation (ABS) paradigm to achieve a hybrid model that allows a detailed description of the OHCA events and a detailed evolution of the police officers' motivation and training level. In the project some interesting aspects that have not yet been approached in the literature about agent modelling are addressed, these are the complete modelling of a police officer as an agent from an ABS perspective in an extra-hospital emergency context, the explicit modelling of knowledge acquisition and loss processes related to infrequently used skills, such as CPR or defibrillation, and the explicit definition of a OHCA survival function that includes the training level of the first responder.

The project is structured in five chapters. The first chapter is called preliminary and it is formed by three sections, the first one explains the medical context of the modelled problem, this is, what is an OHCA? what results are known about the survival probability? what results are known about the intervention of the local police as first responders?. The second section summarizes some of the DES and ABS models that have been used in the literature to model this specific problem and some DES and ABS hybrid models applied to different problems. The last section of the chapter details the main objectives of this project.

Chapter 2 is called methodological framework and it is divided into three sections. The aim of this chapter is to briefly explain the theory needed to understand the developed model. The first section is devoted to geographic representation of points and distance calculation between geographic points. The second section does an introduction to the DES paradigm and the third section to the ABS one. The fourth section does a brief introduction to graph theory, used to model the relationships between the agents.

Chapter 3 is the main chapter of the project and it is divided into four sections. The first section explains the DES submodel, it is explained why the DES paradigm is used and what for, the events that are going to be modelled and some additional problems encountered when developing the model. In the second section the ABS submodel is explained together with the reasons why ABS is needed, in addition, the agents are defined, the knowledge acquisition and loss processes are modelled, the influence of the training level in the survival function is defined and, finally, the interaction between agents is specified. The third section of the chapter is devoted to explain the proposed hybrid model, which combines the DES and the ABS submodels.

Chapter 4 applies the model to a real scenario, validates the model, conducts a sensitivity analysis through an alternative scenario and analyzes the results. Chapter 5 includes the conclusions and future lines of works.

Chapter 1

Preliminaries

1.1 Context

Out-of-Hospital Cardiac Arrests (OHCAs) have been an issue of interest to many researchers and public organizations during the last decades. A cardiac arrest is the sudden and potentially reversible stop of cardiac and pulmonary activity, accompanied by unconsciousness of the patient, which if not treated rapidly leads to death (Asociación Española de Enfermería en Cardiología, 2018).

According to the results of the EuReCa ONE (an international European project for collecting and analyzing resuscitation events during October 2014) (Gräsner et al., 2016), in Spain, 28 out of every 100000 inhabitants suffer an OHCA per year, this is more than 13200 OHCA cases each year. 90% of those cases result in the death of the patient (Daya et al., 2015). The Spanish Nurse Association in Cardiology, on the other hand, states that in Spain happen 30000 OHCAs per year, with a survival rate of 5% (Asociación Española de Enfermería en Cardiología, 2018).

After a cardio-pulmonary arrest the patient can suffer irreversible organ damage after 4 to 7 minutes from the time the circulation has stopped and no oxygen reaches the heart or the brain (Niles et al., 2011). The main factors that increase the survival probability are rapid initiation of CPR by a bystander and rapid defibrillation of the patient (Hirsch et al., 2012). Providing cardiopulmonary resuscitation (CPR) during the first five minutes is essential to maximize the patient's survival probabilities. According to Eisenberg et al. (1979b) if basic CPR is given within the first 4 minutes and advanced CPR (which includes defibrillation) within 8 minutes then the survival probability of the patient reaches 43%. However, if the basic CPR is maintained within the first 4 minutes but the advanced is delayed until minute 16, then the probability decreases to 10%. Finally, they show that if the basic CPR takes longer that 4-5 minutes to initiate then the patient's survival to the OHCA it is very unlikely. Ko et al. (2020) concluded that every minute elapsed from cardiac arrest to initiation of CPR means a 9% reduction in the patient's correct neural recovery, moreover, after 10 minutes the patient is highly likely to have died (Larsen et al., 1993). In addition, it is shown (Eisenberg et al., 1979a, Roth et al., 1984) that in patients with ventricular fibrillation, time until the defibrillation is the main survival factor. Therefore, prompt assistance to an OHCA patient is vital to improve their chances of survival.

The majority of OHCA survivors are found among patients with a witnessed cardiac arrest (Holmberg et al, 1998), this is, chance of survival is much lower if OHCA is not witnessed. Only 17.9 % of the patients that suffer a cardiac arrest in the street (in the USA) survive (McNally et. al, 2011). Currently a third of the OHCAs in the USA are attended by pedestrians (Sipsma et al., 2011). According to Angulo-Menéndez and Pérez (2017) the percentage of citizens with specific CPR training varies between 20% and 75% depending on the country and the sample.

The first action guidelines for OHCAs where published in 1966 by the American Association and in 1976 by the American Heart Association (AHA) (American Heart Association, 2020), since then, they have been reviewed constantly. The AHA 2020 guidelines (American Heart Association, 2020) establish that when a bystander witnesses an OHCA, he/she should follow these steps: call the emergency services (112 in Spain), recognise that the patient has suffered an OHCA (i.e., is unconscious and does not breath nor has heart beat), start a CPR (if the emergency services recommend it), send someone search for a defibrillator, defibrillate the patient (either a bystander, the emergency medical services (EMS) or other no EMS agents such as local police), give the patient advanced resuscitation (by the EMS), take the patient to the hospital (ambulance) and, finally, give the patient post-cardiac arrest care.

In the early 90s' the concern about out-of-hospital cardiac arrests led the AHA to promote the acquisition of public automatic external defibrillators (AEDs) that could be used by pedestrians. The positive results of numerous experiments, such as the one led by Hallstrom et al. (2004), fostered the massive placement of public AEDs in cities all around the world. The general population's limited knowledge about OHCAs and proper action protocols has resulted in infrequent use of these defibrillators, as highlighted by Yoon et al. (2016). They denounce in their study that in the Korean city of Busan (approx. 3 million inhabitants) only 15 public AEDs have been used since the installation of 206 devices in 2007. This usage ratio indicates that each public AED was employed once every 26.3 years. This is a problem from a healthcare perspective, because the EADs are not being used to save lives, and from an economic perspective, because these unused devices need an annual maintenance with the corresponding costs. Another existing problem with the public EADs is their location (Aeby et al., 2020), they usually do not provide an optimal coverage of the city, because they are located in public buildings which is not necessarily an optimal distribution.

Several proposals have been made to improve the use of defibrillators, for example Derkenne et al. (2020) proposed training groups of voluntaries that could be alerted by the emergency services when an OHCA occurs. These voluntaries will be able to respond rapidly and provide early and high quality CPR and defibrillation to the patient. Another approach involves equipping the local police with AEDs and giving them training sessions on CPR and defibrillation. Although police officers are not specialized medical personnel, it is highly probable that they will be required to perform a CPR or defibrillate an OHCA patient as first responders (Police Statistics Annual Report, 2018). Police officers represent a special type of potential first responders for medical emergencies, because they patrol large networks of streets, roads and highways. According to the CDCP (Centers for Disease Control and Prevention) 20% of the out-of-hospital cardiac arrests take place in public places, 25% of those take place in the street or on roads (McNally et. al, 2011). Police officers reduce the time until the first discharge and are therefore a decisive type of first responder.

In Spain, local police patrols are often activated by the emergency services to ease the work of the EMS. In addition, often police cars arrive at the scene before the ambulances do (Mosesso et al., 1998). According to the study of Waalewijn et. al. (1998) in 19% of out-of-hospital cardiac arrests police officers act as first responders, with a response time of 3 minutes, compared to 8 minutes for emergency services. Husian and Eisenberg (2013) showed that when police officers provide the first discharge to the patient, the survival probability increases, even compared to the emergency services (39.4% vs 28.6%). White et al. (1994) and Blom et al. (2014) also proved that equipping local police cars with EADs significantly improves the survival probability of OHCA patients. More specifically, Blom et al. (2014) demonstrated that the recovery probability increases from 29.1% to 41.4 %. Myerburg et al. (2002) also found similar results: equipping local police with AEDs reduces the response time and increases the survival probability of patients.

Previous research (Kooij et al., 2004 and White et al., 2005) has shown that police officers can be trained to effectively operate AEDs and that these training programs are cost-effective. The efficacy of OHCA resuscitation can be maximized when EMS (or police officers) maintain competency in the skill and knowledge of resuscitation. If the quality of CPR is poor, survival rates decreased. This is, there is a direct relationship, between the quality of the CPR performance and the patient's survival probability (Soar et al, 2010). For all these reasons, police officers should be trained more frequently than other non-medical personnel. Studies (Fan et al, 2016) have shown that repeated training helps to retain CPR knowledge and achieve better results in practice.

The previous studies have demonstrated the impact of police intervention on the survival probability of OHCA patients and the significance of maintaining police officers with a high level of training. However, it is important to note that these results have been qualitative, conceptual, or quantitative based on statistical studies. In this project, a hybrid simulation model is proposed to allow for testing different training programs and conduct a detailed analysis of the knowledge acquisition and loss processes experienced by police officers during CPR and defibrillation training sessions. This is, we will carry out the translation of medical and statistical results into a simulation model, enabling us to test different scenarios that would otherwise be impractical to explore.

1.2 State of Art

Simulation paradigms have been widely used to model healthcare related problems. Gunal (2012) provides an exhaustive guide for building hospital simulation models. In that guide it is explained how to model a hospital system following the three main simulation paradigms: Discrete Event Simulation (DES), System Dynamics (DS) and Agent Based Simulation (ABS). These paradigms are the three main simulation methods used in health care modelling. DES is the oldest and most used of the three and is used to model systems that change states dynamically, stochastically, in discrete intervals; SD is a popular method for modelling continuous systems, based on flows; ABS is a simulation method for modelling dynamic, adaptive, and autonomous systems from the perspective of the constituent elements (agents) of the system. The vast majority of developed models use only one of these approaches, however some models combine two of them. Chahal and Eldabi (2008) discuss the combinations of simulation methods in healthcare domain and propose three types of hybrids: 1) hierarchical mode, where two different simulation models work off-line and one feeds the other, for instance, a DES model feeds a SD model; 2) process environment, where two different models are used but one of them includes the other, for instance an ABS model resides inside an SD model; and 3) integrated mode, where there is a single model that integrates various simulation paradigms working in-line. The model developed in this project is an integrated DES-ABS model, so only DES, ABS and combinations of both (applied to the healthcare domain) will be discussed in the following.

Applications of DES models in healthcare domain are abundant. DES models have been used to analyze and optimize the availability of resources in hospitals: Garcia-Vicuña (2022) used a DES model to predict the availability of Intensive Care Unit (ICU) beds during the COVID-19 pandemic and that way support decision-making for the short-term planning of hospital resource needs. Paul and Lin (2012) analyzed with a DES model the main factors that cause overcrowding in hospital emergency departments and tried to identify strategies to resolve them. DES models have also been employed to study the interactions among the departments that constitute a hospital: Gunal and Pidd (2007) created a system of four interconnected DES models of emergency, outpatient, and inpatient departments of a hospital. They developed one DES model for each department, that joined formed one last DES model for the whole hospital. The study of patient flows in hospital departments is also a commonly approached via DES models: Genuis and Doan (2013) studied the effect of medical trainees on pediatric emergency department flow, this is, how the amount of medical trainees affects patient wait time, total length of stay, and rates of patients leaving without being seen for pediatric emergency department. Finally, DES paradigm is also commonly used in epidemiology: Viana et al. (2014) proposed a DES-SD composite model for modelling Chlamydia infection. This model is of the type " process environment", this is, there is a big SD model, which models the propagation of the disease among the population, that includes a small DES submodel to model the patients' flow through Genito-Urinary Medicine Clinics.

Discrete event simulation has also been used to model out-of-hospital cardiac arrests related problems. Wei Lam et al. (2014) used a DES model to reduce the ambulance response times in Singapore. Aguiar et al. (2022) used DES and genetic algorithms to estimate the necessary resources to respond in a timely manner to out-of-hospital emergencies in Bogotá. Andreev et al. (2013) proposed a DES model to study sudden cardiac death (SCD), which can be caused by an OHCA, and to identify interventions and the optimal time of intervention leading to high potential impact on SCD risk reduction. Strauss et al. (2021) developed a rule-based DES model to optimize emergency medical structures (EMS), they studied the particularities of the emergency services of different countries and addressed the location and relocation of ambulances, dispatching and routing policies, and EMS interplay with other players in prehospital care.

Since the 1990s there has been a great interest in the potential of the ABS models, an example of that are the numerous Winter Simulation Conference's tutorials devoted to ABS: Macal & North (2006), Macal & North (2009), Kasaie & Kelton (1015) and Macal (2018). ABS models have a lot of use in the healthcare domain. Epede (2020) proposed an ABS model to model and simulate the transmission of flu virus contact in Emergency Departments. Fragapane et al. (2019) developed an innovative agent-based simulation to model hospital logistics. Sibbel and Urban (2011) conducted another study that modelled the management of a hospital using the ABS approach. Other studies (Stainsby et al., 2009 and Cabrera et al, 2011) have proposed models to simulate and optimize hospital emergency departments using

ABS. Another use of ABS has been to simulate emergency evacuations: Pan et al. (2007) used agents to simulate human and social behaviors in evacuations and Christensen and Sasaki (2008) considered evacuations with individuals with disabilities in the population. Unlike DES models, we have not been able to find any ABS models used to simulate OHCA problems.

Combined ABS and DES models are not very common, but some of them can be found in the healthcare literature, most of them from the annual Winter Simulation Conference. The problem is that some of the models that are labelled as hybrid do not satisfy the necessary requirements to be considered ABS (see Section 2.3). Vieira (2010) developed a DES model combined with small world networks to model the propagation of VIH in the society, some authors (Gunal, 2012) have considered this an ABS-DES model because each node of the network has a different evolution in time and represents an individual person, however the model lacks an individual characterization of the agents with attributes and methods, that is why we argue it is not accurate to classify it as an ABS model. Sanchez and Sanchez (2015) developed scalable discrete event stochastic agent-based model of infectious disease propagation. They used a DES approach to model each agents' infection and recovery processes and the interaction between agents was modelled without a network. Anagnostou et al. (2013) developed a distributed hybrid agent-based discrete event simulation model within the context of emergency medical services (EMS). The agents of the model are the ambulances and the DES is used to model the accidents and the emergency departments. Augusto et al. (2016) evaluated discovered clinical pathways using process mining and joint agent-based discrete-event simulation, this is, they developed a hybrid DES-ABS model to extract knowledge from an existing hospital database through simulation and to study the impact of medical decisions. No hybrid DES-ABS model has been found to model OHCAs.

Another aspect we are interested in modelling in this project are the knowledge acquisition and loss processes a police officer experiments after attending a CPR and defibrillation training sessions. Skills acquisition and loss processes have been studied in psychology and also from a mathematical modelling perspective. Murre et al. (2013) developed a general forgetting model called *the memory chain model*, which, based on previous studies in the fields of medicine and psychology, proposes that memory is stored in several processes chained one after the other, so that each higher level is forgotten more slowly than the previous one. Knowledge is continuously copied from one layer to the next, but in the process it is lost in such a way that the layers that retain the most (higher layers) are the ones in which the least information is recorded, because they are the last in the memory chain. Knowledge loss is assumed to follow an exponential decay, however Murre et al. (2013) mentioned that the exponential nature of the decay, although being the most commonly assumed, it is not critical for the working of the model. Murre et al. (2013) also commented that the exponential decay approach does not consider the results of Stickgold et al., (2000), which proved that in cases of high consolidation rates there may be a temporary increase in total intensity and hence recall probability, after that it will stabilize and exponentially decay.

1.3 Objectives

The objectives of the developed hybrid model in this project, which analyzes the impact of training police officers on OHCA survival, are as follows:

1. Reinforce all the previous results (Mosesso et al., 1998; Waalewijn et. al., 1998; and Myerburg et al., 2002) that show that local police is usually faster than the ambulances and plays an important role in OHCAs attendance.
2. Emphasize the importance of training police officers in CPR techniques and in defibrillation, which translates into a significant increase in the probability of survival of patients who suffer out-of-hospital cardiac arrest.
3. Develop a flexible model that allows the comparison of different training schemes, which combine voluntary and obligatory training session. This way, optimal training schemes that balance costs and police officers' training level can be found.
4. Highlight the potential and the necessity of combining discrete event and agent based paradigms to model real emergency systems, in which the individual attributes of the first responder can have a decisive influence in the patient's survival.
5. Develop an innovative, complete and coherent with the previous ABMS literature, definition of a police officer as an ABS agent in the context of attending OHCAs. Paying special attention to the modelling of the knowledge acquisition and loss processes and the variation of the police officers' motivation.
6. Validate the model with real data and with literature results, so that, the results can be used in real contexts and support decision making in OHCA related issues. This way, the developed model aims to have a social impact.

Chapter 2

Methodological framework

2.1 Geographic coordinates and distance calculation

Due to the fact that in this project terrestrial maps are going to be used, we consider necessary a small introduction to how can points be represented in a map. According to Fernández-Coppel (2010) there are two main ways to represent a point in a map, either the point is represented via the geographic coordinates (Latitude-Longitude) or it is represented using the cardinal coordinates (x,y) with the UTM (Universal Transversa Mercator) projection. There are also other projections that are not universal, such as ESPG:25830, which is used to represent the Iberian Peninsula (the far western part of the peninsula is represented using ESPG:25829 and the far eastern using ESPG:25831). These different projection systems depend on how is the earth surface projected into a geometric form (a plane, a cone or a cylinder) and where are the tangential points between the form and the Earth surface located. In this project we are going to use the geographic coordinates.

The geographic coordinates define each point as a pair of values, latitude and longitude, which are expressed in sexagesimal degrees. This representation system needs a related reference system. First, we consider the line that joins the North Pole and the South pole as the Earth axis. Second, the meridians are defined as the intersection of the infinite planes that contain the Earth axis with the Earth surface. The Greenwich meridian (the one that passes through the city of Greenwich in the UK) is considered the meridian of reference, i.e. 0^{o}. Finally, the parallels are defined as the lines of intersection between the Earth surface and the perpendicular planes to the Earth axis. The reference parallel is the Equator, which is the parallel with the greatest distance to the Earth center. Figure 2.1 shows how to calculate the geographic coordinates of point P using the previously defined reference system, λ is the latitude of P and γ is its longitude. Latitude represents the angle formed between the parallel where point P is situated and the equator. Similarly, longitude indicates the angle between P's meridian and the Greenwich meridian.

Once we know how to represent points in a map, the next step is to calculate the distances between them. One first approximation could be to use the euclidean distance. The euclidean distance between two points (x_1,y_1) and (x_2,y_2) is defined as $\sqrt{(x_1-x_2)^2+(y_1-y_2)^2}$; this distance measures the length of the straight line between the two considered points. It is important to notice that, when using geographic coordinates, the value of the euclidean distance is also measured in sexagesimal degrees. The euclidean distance may not be a good option to measure the distance between two points of the Earth surface, because it considers a straight line between the points and ignores the Earth curvature. However, if the studied area is small (compared to the Earth surface), then it can be assumed that the studied area is almost flat and the euclidean distance is acceptable. The model proposed in this project takes place in a city, so the area can be considered sufficiently small.

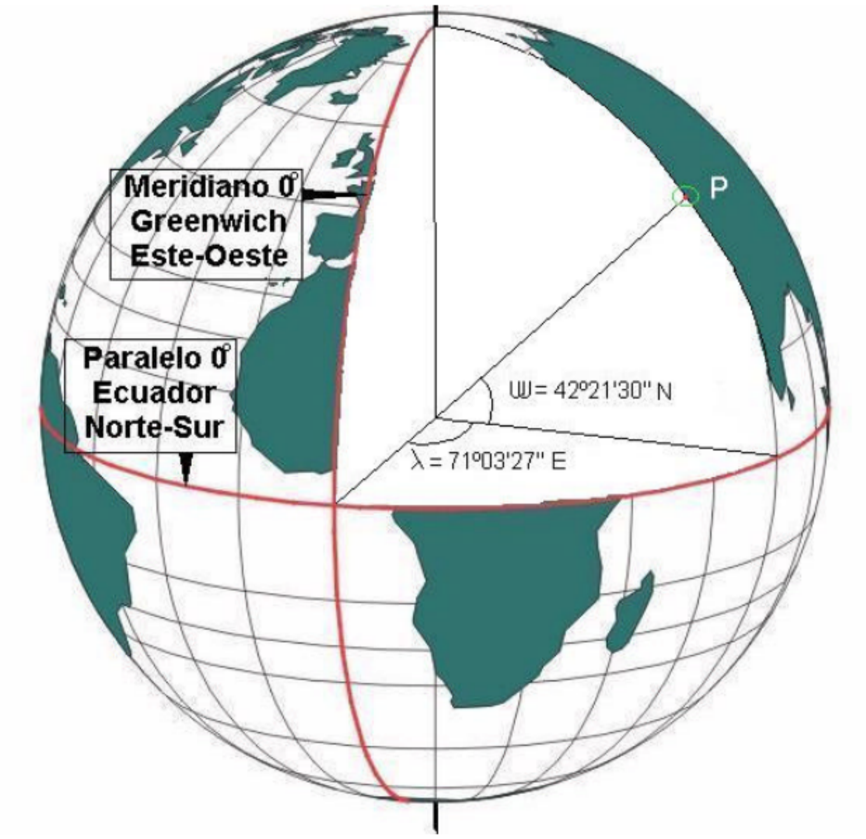


Figure 2.1: Calculation of longitude and latitude of the point P

Some times it is going to be necessary to translate sexagesimal degree variations to kilometers variations, for instance, when calculating the coverage of a public automatic external defibrillator. It is important to notice that, due to the definition of meridians and parallels, a displacement of one longitude degree is much greater (in terms of kilometers) in the Equator than in the North Pole. On the other hand, changes in latitude are homogeneous all around the Earth (considering the Earth surface smooth). The equations that relate degrees with kilometers are the followings:

$$Latitude: \quad 1^o = 111.111\ km \tag{2.1}$$

$$Longitude: \quad 1^o = 111.320 * \cos(latitude)\ km \tag{2.2}$$

Equation 2.1 is obtained dividing the distance between the North Pole and the Equator (aprox. 10000 km) by 90º, as a result each latitude degree represents 111111 km. Equation 2.2

is obtained dividing the circumference of the Earth in the Equator (aprox. 40075 km) by 360º, so each degree in the Equator is equal to 111320 km; this result must be corrected with the latitude, that is why a cosine appears in the formula. Note that, in the Equator latitude=0º and $\cos(0) = 1$, so no correction is made.

Leaving aside the geographic considerations, the euclidean distance is not always the best option. In this project it will be necessary to calculate distances between the location of police officers, ambulances or pedestrians and the location of Public AEDs or the location of OHCAs inside a city. It is easy to realize that the euclidean distance becomes a bad option when computing distances inside a city, specially when car routes are considered, because city roads do not join city points with straight lines. An alternative, could be to use the Manhattan distance. The Manhattan distance between two points (x_1, y_1) and (x_2, y_2) is given by $|x_1 - x_2| + |y_1 - y_2|$. This distance is a better approximation to what displacements in a city look like, specially when considering cities with a gridded layout, because it reflects the need of bordering the buildings that appear in the path between the two considered points (while the euclidean distance will pass directly through those buildings). However, the Manhattan distance is still an approximation and does not consider the specific layout of the considered city. A better approximation is to use a road network, this way almost real walking and driving distances can be computed. This is because road networks take into account the direction of each road and are very detailed. Boscoe et all. (2012) showed that, in no emergency related scenarios, there is no significant difference between using euclidean distance or road network distance when computing distances within a city. Nevertheless, we consider that when studding an emergency scenario (OHCA), in which each minute is essential and could make a significant difference in the patient survival and recovery, it is important to use the most accurate method available to compute the distances. There are many road networks available on the internet, some of them are open sourced while others are private, in this project Open Street Maps (OSM) is going to be used, because it is free and open source. The OSM severs are going to be accessed via the *pandana* library in *Python*.

Nevertheless, road network based distances have also some limitations. First, the computational cost of calculating a distance is high, because a petition to the OMS server is involved in the process, while computing an euclidean or Manhattan distance involves a simple local arithmetic calculation. In this project, to solve that issue the *Python* library *pandana* is used. This library uses a simplified OSM network which is required to be loaded only once per execution. This allows to make a lot of calculations in a short amount of time, but with a small lose of precision, because the network is smaller, so it has less nodes. The nodes in the network represent the points in the map where a car (pedestrian) can be, so, when a distance between two points is requested, actually the distance between the nearest nodes to each of those points is computed. Naturally, different networks are used to compute walking and driving distances.

2.2 Discrete Event Simulation (DES)

In this section we introduce briefly the Discrete Event Simulation (DES) paradigm (Law, 2015). This introduction is divided into three parts, a general insight into the DES paradigm, a brief explanation of the time advance mechanism and a detailed description of the components that form a DES model and the interaction between them. Additionally a fourth part is included in which homogeneous Poisson processes will be explained, these processes will be used to generate the OHCAs. The DES paradigm will be utilized to model the incidence of OHCAs and the implementation of CPR and defibrillation training sessions. Poisson processes will be employed to simulate the timing of OHCAs.

General insight

Discrete event simulation is a stochastic modelling approach ideally suited to model a system in which the state variables change instantaneously at separate discrete points in time, these type of systems are, generally, too complex to be approached analytically. The points in time, in which the state variable change are the ones at which an event occurs. An event is defined as an instantaneous occurrence that may change the state of the system, we say *may* because an event might be used (for instance) to schedule the end of a simulation run at a particular time or to schedule a decision about a system's operation at a particular time and might not actually result in a change in the state of the system. Although a DES model could, theoretically, be done by hand calculations, in practice DES models involve a huge number of data and calculations which require it to be treated with a computer.

Time-Advance mechanism

Because of the dynamic nature of the DES models it is necessary to define a mechanism to keep track of the current simulation time and to advance the simulation time from one event to the next. The variable in a simulation model that gives the current value of simulated time is called the **simulation clock**. The unit of time of the simulation clock is never stated explicitly, it is assumed to be in the same units as the input parameters. In addition, there is usually no relationship between the simulated time and the time needed to run the simulation in a computer.

There are two main strategies when it comes to advance the simulation clock: next-event time advance and fixed-increment time advance. The former is the most commonly used and the one that is going to be used in the proposed model in this project, this is why it is the only one that we are going to explain. With the next-event time advance, the simulation time is initialized at 0 and the time of occurrence of future events are determined and saved in the event list. Then the simulation clock is advanced to the most imminent event, this is the event that occurs closest to the current simulation time. Next, the state variables are updated (depending on the event) and the event list is updated with the next time an event of that type will occur. Then, again, the simulation clock advances to the time of the new most imminent event and again the system state is updated. The cycle continues until some predefined stopping condition is satisfied. State changes occur only at event times, so, by jumping the simulation clock from time event to time event the periods of inactivity are skipped and computational resources are saved, which does not happen with the fixed-increment time advance approach.

Components of a DES model

DES models have been applied to a huge variety of real-world systems, nevertheless all of these models share the same basic components and the same logical organization of these components. If the next-event-time approach is used then the elements that form a DES model are:

- **System state**: The collection of state variables necessary to describe the system at particular time.
- **Simulation clock**: A variable giving the current value of simulated time.
- **Event list**: A list containing the next time when each type of event will occur.
- **Statistical counters**: Variables used for storing statistical information about system performance.
- **Initialization routine**: A subprogram to initialize the simulation model at time 0.
- **Timing routine**: A subprogram that determines the next event from the event list and then advances the simulation clock to the time when that event is to occur.
- **Event routine**: A subprogram that updates the system state when a particular type of event occurs (there is one event routine for each event type).
- **Library routines**: A set of subprograms used to generate random observations from probability distributions that were determined as part of the simulation model.
- **Report generator**: A subprogram that computes estimates (from the statistical counters) of the desired measures of performance and produces a report when the simulation ends.
- **Main program**: A subprogram that invokes the timing routine to determine the next event and then transfers control to the corresponding event routine to update the system state appropriately. The main program may also check for termination and invoke the report generator when the simulation is over.

The relationships among these components are represented in the Figure 2.2. At the start of the simulation the main program calls the initialization routine, which sets the simulation clock to 0 and initializes the system state, the statistical counters and the event list. Then the main program regains control and invokes the timing routine to know which is the next event that takes place, the timing routine also advances the simulation clock to the time of the next event. Then the main program invokes the event routine of the correspondent event. The event routine updates the state of the system, updates the statistical counters and adds to the event list when will the next event of that type occur, to do so, generally it is necessary to generate random variables (which follow a known random distribution) using the library routine. Once the event routine has ended it is checked whether or not the end of simulation condition is satisfied. If it is not satisfied the main program regains control and calls the timing routine (this cycle is repeated until the termination condition is satisfied), if it is satisfied the simulation ends and the report generator is invoked to compute the estimates of interest.

DES models can be classified into two big groups depending on the nature of the termination condition, models can be with termination point or without termination point. In the first ones, there is a natural event that provokes the end of the simulation and restarts all the system's state, for instance when a supermarket's queues system is modelled the closure of the supermarket can be considered a natural system restarting event, because each day the queues restart at 0 clients. In the second ones, there is not an event that determines the end of the simulated process, in this cases what is interesting is to study the long-term behaviour of the system and see if the system converges to a stationary state. The period until the system reaches the stationary state is called transitory state. In this project the DES model considered has no natural termination point.

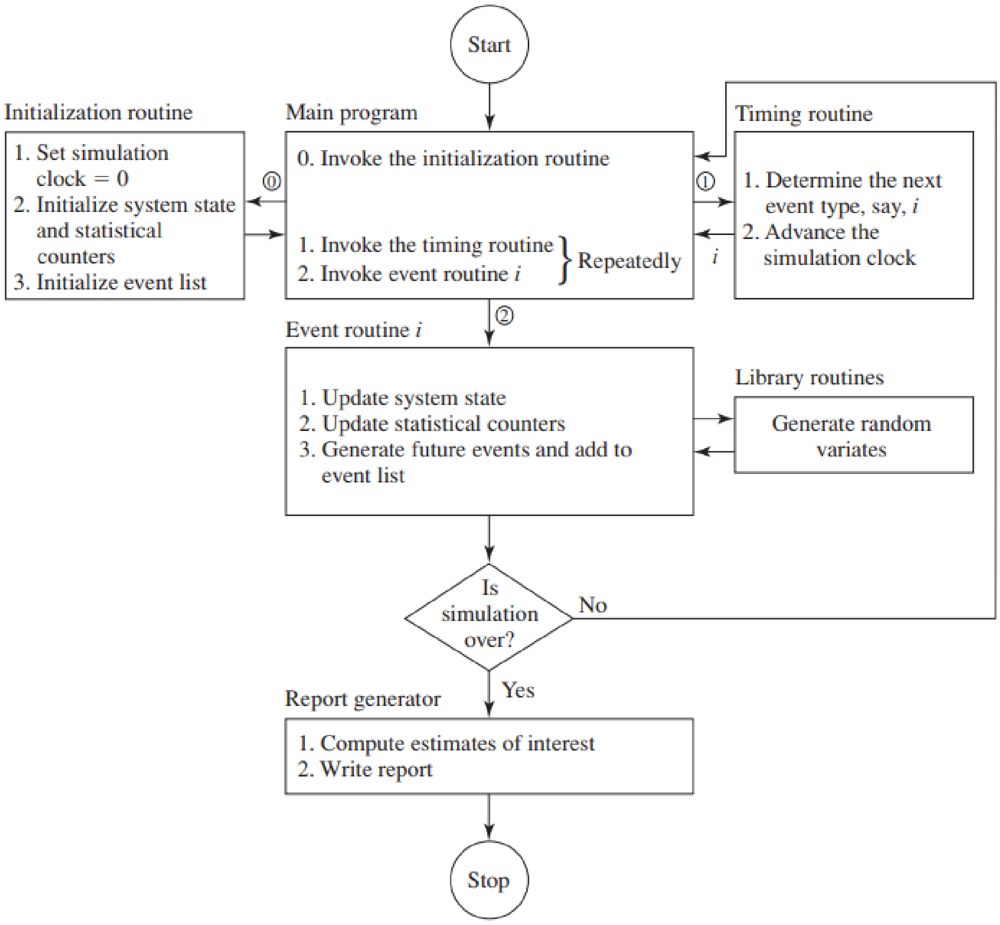


Figure 2.2: Flow of control for the next-event time-advance approach (Law, 2015).

Homogeneous Poisson processes

In this subsection we are going to define stationary Poisson processes, which are commonly used in DES models to simulate arrival processes, for instance costumers arrival. In the proposed model they are going to be used to simulate the occurrence of OHCAs. So, in the following definitions, instead of customer arrival one should think of OHCA occurrence.

Definition 2.2.1. The stochastic process $\{N(t), t \geq 0\}$, where $N(t)$ is the number of customer arrivals until time t, is said to be a *Homogeneous Poisson Process* if:

1. Customers arrive one at a time.
2. $N(t+s) - N(t)$ (the number of arrivals in the time interval $(t, t+s]$) is independent of $\{N(u), 0 \leq u \leq t\}$.
3. The distribution of $N(t+s) - N(t)$ is independent of t for all $t, s \geq 0$.

Properties 1 and 2 are satisfied by many arrival processes. Property 1 implies that customers do not arrive in batches (more than one at the same time). Property 2 implies that the number of arrivals in a given period of time $(t, t+s]$ is independent of the number of arrivals from the beginning of the simulation to some time u before s, this is, the number of previous arrivals does not influence the number of arrivals in a given period of time. This property could be violated if, for instance, a large number of arrivals in $[0, t]$ caused some costumers arriving in $(t, t+s]$ to go away immediately because they find the system highly congested. The third property is the most restrictive one, since it implies that the arrival rate does not depend on the time of the day, the month of the year etc., this is, at any time interval of length s the arrival rate of customers is the same. If the third property is not satisfied then it is a no homogeneous Poisson process.

The following theorem, proved in Çinlar (1975), explains where the Poisson process gets its name.

Theorem 2.2.1. *If $\{N(t), t \geq 0\}$ is a Poisson process, then the number of arrivals in any time interval of length s is a Poisson random variable with parameters λs (where λ is a positive real number). That is*

$$P[N(t+s) - N(t) = k] = \frac{e^{-\lambda s}(\lambda s)^k}{k!}, \qquad for \;\; k = 0, 1, 2, ... \;\; and \;\; t, s \geq 0.$$

Therefore, $E[N(s)] = \lambda s$ (because the expectation of a Poisson random variable with parameter λ is λ), and, in particular $E[N(1)] = \lambda$. Thus, λ is the expected number of arrivals in any interval of length 1. λ is called the rate of the process. We now see that the interarrival times for a Poisson process are independent and identically distributed (IID) exponential random variables, the theorem is proved in Çinlar (1975).

Theorem 2.2.2. *If $\{N(t), t \geq 0$ is a Poisson process with rate λ, then its corresponding interarrival times $A_1, A_2, ...$ are IID exponential random variables with mean $1/\lambda$.*

2.3 Agent Based Simulation (ABS)

In this section we are going to introduce the Agent Based Modelling and Simulation (ABMS). We are going to base our introduction to ABMS on four tutorials of the Winter Simulation Conference: Macal and North (2006), Macal and North (2009), Kasaie and Kelton (2015) and Macal (2018). The ABMS paradigm will be employed in the proposed model to represent police officers, capturing the evolution of their attributes over time, their interactions with one another, and their interaction with OHCAs and training sessions.

The Agent Based Modelling and Simulation (ABMS) is a relatively new approach to modelling systems based on autonomous agent interaction. Autonomous means that the agents have programmed behaviours that allow them to decide and act inside a simulation context, depending on which situation they are in. There is no central authority nor a global objective function that controls the agents behaviour. ABMS has its origins in the field of the multi-agent systems (MAS) and in the IA-robotics field. However, the aim of ABMS is not limited to the design and understanding of "artificial agents", but its main objective is to model human social behaviour and individual decision making processes (Bonabeau, 2001).

The appearance of the new ABMS paradigm responds to four main factors:

- The systems that have to be modelled are increasingly getting more complex in terms of interdependence between components.
- Some systems (like markets) have always been too complex to be accurately modelled using traditional paradigms
- More and more data is getting organized into databases at finer levels of granularity.
- Computational capacity is growing rapidly allowing to create more complex models.

Historically it can be said that the origin of the ABMS models is in the Complex Adaptive Systems (CAS). These systems aim to answer the question: how complex behaviors arise in nature among myopic, autonomous agents? This is, how simple rules can lead to complex emergent behaviours. One typical example of these systems is the Boids model (Reynolds, 2006), a Boid is an agent whose behaviour is similar to the one of a bird. This agents, with only three very simple rules:

1. Cohesion: each agent steers toward the average position of its nearby "flockmates".
2. Separation: each agent steers to avoid crowding local flockmates.
3. Alignment: each agent steers towards the average heading of local flockmates

give rise to complex flock behaviour, that was not initially expected. This is, knowing the three simple rules that define the behaviour of each Boid, one could no expect the global flock behaviour of the system. Two main conclusions can be extracted from this example: (1) Complex patterns that last in time can emerge in systems that are completely determined be simple deterministic local rules. (2) The patterns that arise can be extremely susceptible to the initial conditions of the system. In this project we want to study what trends emerge in the behavior, motivation and training level of police officers and their influence in the survival of OHCA patients when different training programs are applied, having defined by means of simple rules the learning processes of the agents.

Every ABMS model has three main components:

- **Agents**: with their attributes and behaviours.
- **Relationships**: between agents and interaction methods. A **topology of contacts** define how and with whom interacts each agent.

- **Environment**: Agents live in and interact with the environment, in addition to their interaction with other agents.

Although there is not a universally accepted definition of agent, most definitions coincide in the same basic aspects. Some authors consider that any independent component of a system is an agent. Others defend that the behaviour of these components need to be adaptive in order to be considered an agent. Casti & Berry (1997) established that agents needed to have two type of rules: basic behavioural rules that control their response to the environment and other agents' actions and high level behavioural rules that govern how the basic rules change, and therefore describe how agents adapt to changes. Jennings (2000) highlights the importance of agents having autonomous behaviour, i. e., the absence of a central authority. Summarizing all the important aspects that different authors have emphasised, an agent must have the following characteristics:

- Autonomy: Every agent is autonomous and self-directed. An agent can function independently in its environment and in its interactions with other agents, generally in a limited range of situations. The behaviour of an agent refers to a process that links the information an agent receives with its decisions and actions.
- Modularity: Every agent is modular and self-contained. Every agent is identifiable and discrete, with a set of attributes or characteristics, behavioural rules and the capacity of making decisions. Modularity implies that the agent has a boundary and it can be easily determined whether something (an elements of the model's state) is part of an agent, is not or is a characteristic shared among agents.
- Sociality: Every agent is social and interacts with other agents. Common interaction protocols are: contention for space and collision avoidance; agent recognition; communication and information exchange; influence; and other domain-or application-specific mechanisms.
- Conditionality: Every agent has a state that varies in time. This state is defined by the value of the attributes and the behaviours of the agent in a specific moment in time. The state of an agent-based model is the collective states of all the agents along with the state of the environment. The behaviour of an agent depends on its state. The richer the set of possible states an agent can have, the richer the set of possible behaviours and interactions, and, therefore, the richer the possible emergent behaviours in the system.

There are also some additional characteristics that an agent may or may not have:

- Situated: Agents may interact with their environment as well as with other agents. it is said that an agent is *situated* when its behaviour is situationally dependent, this is, its behaviour its based on the current state of its interactions with other agents and the environment.
- Goals: Agents can have goals they want to achieve related to their behaviours. So the agents modify their behaviours in order to achieve their goals.
- Flexibility: Agents may have the capacity to learn and adapt their behaviour based on their experience. This requires the agents to have some type of memory. An agent can have higher level rules that allow them to change their behaviour.

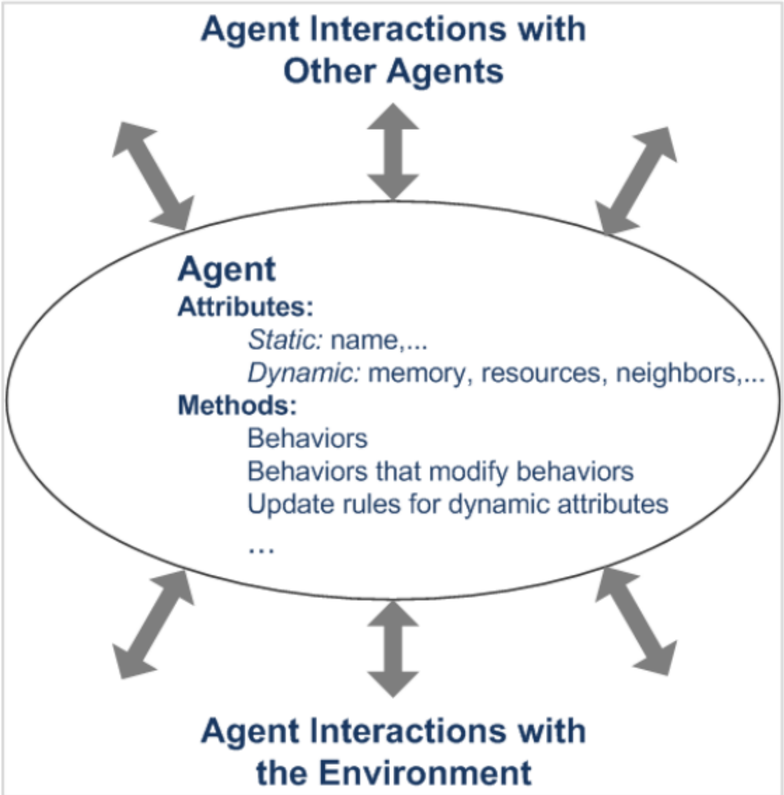


Figure 2.3: A typical agent. Macal (2018).

Figure 2.3 shows an scheme of a typical agent. Summarizing, agents are diverse, heterogeneous and dynamic in their attributes and behavioural rules. This is what differences them from, for instance, a traditional system of particles. Agents are **autonomous, self-contained and interactive**. In our model the agents are going to be the police officers, who are going to be able to make their own autonomous decisions such whether to attend a voluntary training session or not.

In the application of ABMS models to social processes, the agents represent a person or a group of people and the interaction between agents represent social interaction processes (Gilbert & Tritzsch, 1999). Regardless of whether or not agents represent people, one fundamental aspect in ABMS is to model agent interaction (**topology of contacts**), this is, who is connected to whom? and which mechanisms govern the nature of interactions?. For instance, cellular automata models represent interaction via a graticule. However, the more common and general case is to employ a **network** (graph). This network of contacts can be static or evolve in time according to the agents behaviour. Other possible topology of contacts are: Aspatial, agents have no location and the model has no spatial representation, agents that interact are chosen randomly; Euclidean space, which can be 2D or 3D; and Geographic Information Systems (GIS). Regardless of the topology used, the main idea is that the interaction between agents and the transmission of information is local. This means that in a given moment of time the agents interact only with a limited and small number of other agents, compared to the total number of agents of the system. There is no global information shared between agents. In the proposed model the agents are going to interact with each other through static network.

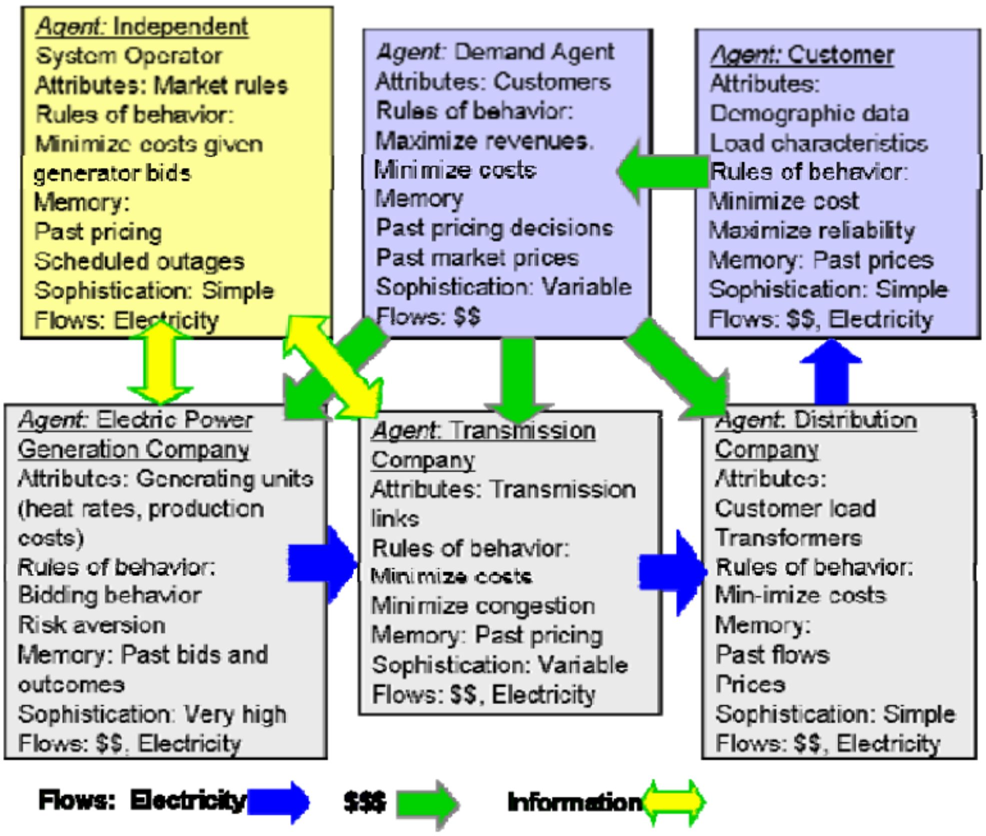


Figure 2.4: Example of a Electricity Market Complex Adaptive System model (Macal and North, 2009).

The ABMS model range from small minimalist models based on idealized assumptions whose objectives are to capture only the most relevant aspects of the system, to big scale models whose objectives are to help in the decision making processes. The latter ones usually include real data and pass trough validation processes in order to ensure the credibility of the results. An example of an ABMS model can be seen in Figure 2.4, it is a Electricity Market Complex Adaptive System, with 6 different type of agents: Independent System Operator, Demand Agent, Customer, Electric Power Generation Company, Transmission Company and Distribution Company. For each type of agent their attributes, rules of behaviour, memory, sophistication and flows are specified.

Once it is clear what an ABMS model is, the next question we need to address is what steps should we should follow in order to build an ABMS model?

The general steps to build an ABMS model coincide with the construction steps of any mathematical model, which are:

1. Identify the model's purpose: What questions is the model going to try to answer.
2. Identify the system's components and the interactions between them. Here system refers to the real system that it is being modelled.
3. Implement the model and apply it to different scenarios, varying the model's parameters

and assumptions.

4. Conduct a sensibility analysis to test the model's robustness.

However, the construction of an ABMS model has some additional steps which are specific of this modelling paradigm:

1. Identify who are the agents and what is their behaviour. Generally the agents are the decision-makers components of the system.
2. Define the environment in which the agents live and interact.
3. Identify the relationships between the agents (the topology of contacts) and define the methods which specify how the agent's attributes (agent's state) change depending on their interactions with other agents and the environment.
4. Define the methods that govern with whom, when and how each agent interacts with the rest of agents.
5. Get the requisite agent related data.
6. Validate the agent's behaviour, in addition to the model's validation as a whole.
7. Execute the model and analyze the output from a micro-scale point of view (the agents) and from a a macro-scale point of view (the whole model).

Currently, it has been observed a gap between traditional simulation theory (mostly developed for DES) and current practice of ABS models in the literature. Some aspects with which one should be careful with when modelling an ABMS model are:

1. Lack of justification for choosing ABMS over other simpler modelling paradigms.
2. Tendency to develop very detailed and realistic models that ignore the tradeoff between the complexity of analysis and transparency of results.
3. Assumptions made by the modelers of the agent's mechanisms and their interactions without explicit validation and consideration of alternatives.
4. Excessively parameter-rich models that need special calibration techniques, that are not usually used by other traditional simulation paradigms such as DES.
5. Unclear definition of the errors of the ABMS model.
6. Specific challenges related to the validation of ABMS models related to their multilevel structure.
7. Specific aspects related to the experimentation and sensibility analysis of the ABMS models.

When developing an ABMS models there are some useful questions the modeler should answer to make sure ABMS is the correct approach to the studied problem, this questions are gathered in Table 2.1. In this project these questions have been answered in Section 3.2.1 to justify the use of ABMS.

Something important to bear in mind is that the answer to the question when should ABMS be used? depends on the question the model is trying to answer and not the other

Category	Questions
Model Purpose /Value added of Agent-based Modeling	What specific problem is the model being developed to address? What specific questions should the model answer? What kind of information should the model provide to help make or support a decision? Why might agent-based modeling be a desirable approach? What value-added does agent-based modeling bring to the problem that other modeling approaches cannot bring?
All About Agents	Who should be the agents in the model? Who are the decision makers in the system? What are the entities that have behaviors? Where might the data come from, especially for agent behaviors?
Agent Data	What data on agents are simply descriptive (static attributes)? What agent attributes are calculated endogenously by the model and updated for the agents (dynamic attributes)? What is the agents' environment? How do the agents interact with the environment? Is agent mobility in space an important consideration?
Agent Behaviours	What agent behaviors are of interest? What decisions do the agents make and what information is required to make such decisions? What behaviours are being acted upon? What actions are being taken by the agents? How would we represent the agent behaviors? By If-Then rules? By adaptive probabilities, such as in reinforcement learning? By explicit heuristics? By regression models or neural networks?
Agent Interactions	How do the agents interact with each other? How do the agents interact with the environment? How expansive or focused are agent interactions?
Agent State	What are the states the agents could find themselves in at some point in time, in the model? Under what conditions do agent states change?
Agent Recap	How do we design a set of experiments to explore the importance of uncertain behaviors, data and parameters? How might we validate the model, especially the agent behaviors and the agent interaction mechanisms?

Table 2.1: Questions that must be answered before creating a ABMS model. Macal (2018).

way around. The most common alternatives to ABMS are SD (System Dynamics) and DES (Discrete Event Simulations). SD models a system as a system of flows whose states change continuously in time. These models are essentially deterministic and based on ODEs (Ordinary Differential Equations) and PDEs (Partial Differential Equations), although randomness could be included by using SDE (Stocastic Differential Equations). DES models systems in which the system states change discretely in time. Both paradigms use an up-to-bottom approach, this means that they represent the system trough a global influence diagram or a flowchart, as a consequence they have very little flexibility when it comes to incorporating individual behaviors.

ABMS, on the other hand, follows a decentralized bottom-to-up approach, this is, the system is described from the point of view of its constitutive elements (the agents) and the system evolution is simulated via the interaction of the agents between them and with the environment. Because of this approach, ABMS provides a much more detailed and realistic description of systems composed of individual heterogeneous elements that interact with each other. However, this gain in accuracy in the model description comes at the cost of an increase in the developing and analysis complexity. This additional complexity is only worthy if it allows a significant increase in the accuracy and validity of the model's predictions. That is why it is really important to choose the correct level of abstraction: the objective is not to create the most detailed model but to develop the best tool to answer the questions of interest assuring the desired precision. When there is not enough available data an over-detailed model gives rise to uncertainty in the results and requires more assumptions to be calibrated. An over-complex model could also be a problem when translating the model's results to a real situation.

ABMS models tend to have a great numbers of parameters. These parameters can be classified into two groups (this classification is valid for all modelling paradigms not only for ABMS). **Fixed** parameters (or given) that are the ones that can be estimated using available data and **free** parameters (or variables) that are unknown and there is no data to adjust them. Generally parameters that can be directly interpreted are preferred over adjusted parameters (Helbing y Balietti, 2013).

To adjust the fixed parameters there is a wide variety of techniques from the DES literature and all of them are applicable to ABMS. When calibrating the free parameters, models with a higher predictive capacity are preferred over models with a higher descriptive capacity, when two models have the same predictive capacity the simpler is preferred (Occam's razor).

In the ABMS models, the model calibration process is complex because these models have multi-scale parameters, these parameters are defined at a local (agent) level, but have a significant global emergent influence in the system. This is why a multi-level calibration approach is needed. Two families of calibration techniques can be distinguished: Black-Box techniques and White-Box techniques.

Black-Box techniques approximate the relationship between the input and the output variables to determine the optimal input configuration. Examples of these techniques are: the gradient descent or the heuristic methods. White-Box techniques make use of explicit knowledge of the system to reduce the configuration of the search space, the complexity of the dependencies between parameters and the computational cost of configuring and evaluating the different possible values for the parameters (Fehler et. al. , 2005).

In ABMS it is very important to study the sensibility of the results to changes in the model's input parameters and to changes in the model's assumptions, i. e., to do a sensibility analysis of the model. To do so DOE (Statistical Design Of Experiments) can be used. This is a systematic approach to design statistically valid experiments and, therefore, to obtain the required information at the minimum computational cost. One usual problem in ABMS sensibility analysis is the fact that the number of free parameters is very high and it is not feasible to do an exhaustive search in the parameters space. This is why methods like the LHS (Latin Hypercube Sampling) are usually used. LHS is a statistic method to generate a sample of possible collections of parameters from a multidimensional distribution, that provides an efficient approach to analyse problems with a huge number of parameters. Heuristic techniques are also efficient alternatives to traditional calibration methods.

Another common problem in ABMS is the choice of factor levers (which values are considered for each parameter): If the range of values considered for an important parameter is too small compared to the range of values considered for a less important parameter, the latter could appear to me more influential in the model than the former (Happe, 2005).

Most of the ideas employed in the DES experimentation, such as the variance reduction techniques, are also needed in ABMS, however they may not be enough.

2.4 Graph theory

In the proposed model, the topology of contacts between the agents is going to be modelled with a graph, that is why we consider interesting to include a small introduction into the essentials of graph theory. Below, some definitions and results are included that are going to be useful when describing agent interaction. All the following information has been extracted from the handbook Gross et. al. (2014).

Definition 2.4.1. A **graph** $G = (V, E)$ consists of two sets V and E.

- The elements of V are called **nodes** (vertices).
- The elements of E are called **edges**.
- Each edge has a set of one or two vertices associated to it, which are called its **endpoints**. An edge is said to **join** its endpoints.

The notation V_G and E_G is used to denote the set of nodes and edges from the graph (G). Visually a graph can be represented as a set of points and lines connecting them, the spatial location of the points may or may not be relevant and the length of the line segments is irrelevant to the meaning. Figure 2.5 shows an example of the representation of a graph.

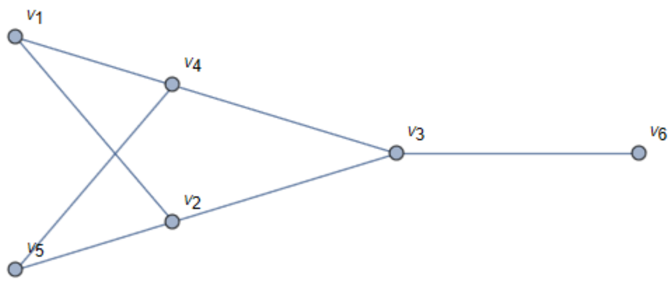


Figure 2.5: Example of a graph

Definition 2.4.2. If vertex v is and endpoint of edge e, then v is said to be **incident** on e, and e is incident on v.
Definition 2.4.3. A vertex u is **adjacent** to vertex v if they are joined by an edge.
Definition 2.4.4. Two adjacent vertices may be called **neighbors**.
Definition 2.4.5. **Adjacent edges** are two edges that have an endpoint in common.
Definition 2.4.6. A **proper edge** is an edge that joins two distinct vertices.
Definition 2.4.7. The **degree** of a vertex v in a graph G, denoted $deg(v)$, is the number of proper edges incident on v plus twice the number of self-loops.
Definition 2.4.8. A **multi-edge** is a collection of two or more edges having identical endpoints.
Definition 2.4.9. A **self-loop** (loop) is and edge that joins a single endpoint to itself.
Definition 2.4.10. A **simple graph** is a graph that has no self-loops or multi-edges.
Definition 2.4.11. A simple graph is a **complete graph** if every pair of vertices is joined by an edge. The complete graph with n vertices is denoted K_n.

Edges can be undirected if $(u, v) = (u, v)$ with $u, v \in V_g$ and $(u, v) \in E_G \iff (v, u) \in E_G$, or directed if $(u, v) \neq (v, u)$, i. e. the order of the endpoints that form the edge is relevant. All the graphs considered in this project are simple and undirected.
Definition 2.4.12. A **walk** in a graph G is an alternating sequence of vertices and edges,

$$W = v_0, e_0, v_1, e_1, ..., e_n, v_n$$

such that for $j = 1, ..., n$ the vertices v_{j-1} and v_j are the endpoints of the edge e_j.

- In a simple graph, a walk may be represented simply by listing a sequence of vertices: $W = v_0, v_1, ..., v_n$ such that for $j = 1, ..., n$ the vertices v_{j-1} and v_j are adjacent.
- The **initial vertex** is v_0.
- The **final vertex** is v_n.

Definition 2.4.13. The **length of a walk** is the number of edges (counting repetitions).
Definition 2.4.14. The **distance between two vertices** in a graph is the length of the shortest walk between them.
Definition 2.4.15. An **adjacency matrix** for a simple graph G whose vertices are explicitly ordered $v_1, v_2, ..., v_v$ is the $n \times n$ matrix A_G such that

$$A_G(i, j) = \begin{cases} 1 & if \;\; v_i \;\; and \;\; v_j \;\; are \;\; adjacent \\ 0 & otherwise \end{cases}$$

For instance, the adjacency matrix for the graph represented in Figure 2.5 is:

$$\begin{pmatrix} 0 & 1 & 0 & 1 & 0 & 0 \\ 1 & 0 & 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 & 0 & 1 \\ 1 & 0 & 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \end{pmatrix}$$

Definition 2.4.16. The **diameter** D of a graph G is $\max_{u,v \in V}\{dist_G(u,v)\}$.

Proposition 2.4.1. *Given a simple graph G and its adjacency matrix A_G. There is a walk of length n from vertex v_i to vertex v_k if and only if the value of the entry (i,k) of the matrix $A_G^n = A_G \times \overbrace{\dots}^{n} \times A_G$ is equal to 1.*

This proposition is going to be used to compute distances between agents easily. The graphs that are going to be used to model agent interactions are going to be random graphs, particularly Edös-Rényi graphs. Let n be a positive integer and let p be a real number, $0 \leq p \leq 1$, and $q = 1 - p$. An n-vertex simple graph G has vertex set $V = [n] = \{1, ..., n\}$. The number of edges in the complete graph K_n is $N = \binom{n}{2}$

Definition 2.4.17. For $0 \leq m \leq N$, the **uniform** (or **Erdös-Rényi**) **random graph**, denoted by $\mathcal{G}(n,m)$, is the uniform probability space on those graphs with exactly n vertices and m edges. Thus, the probability of any n-vertex m-edge graph is

$$\binom{N}{m}^{-1}$$

An Erdös-Rényi simple random graph with n vertices and probability p can be created with the following algorithm:

Algorithm 2.4.1. .

1. *Consider n isolated vertices*
2. *Join each pair of vertices with an edge with probability p*

The agents' network of contacts in the proposed model is going to be a Erdös-Rényi simple random graph without isolated vertices.

Chapter 3

The mathematical simulation model

In this chapter an innovative hybrid model is developed to describe and analyse the impact of training local police in Cardiopulmonary Resuscitation (CPR) and equipping their cars with External Automatic Defibrillators (EADs) on the outcome of Out-of-Hospital Cardiac Arrests (OHCAs). This model combines a DES model, which governs how the OHCAs and the police training sessions are distributed in time, and an ABS model, which allows for an individualized description and evolution of each agent, which influences their decision-making regarding training session attendance, ultimately impacting the probability of survival. The model proposed is innovative in two ways: first, it provides a detailed description of a police officer in a health emergency context from an agent-based perspective; second, it allows a systematic analysis of the impact of the training level of non-professional first responders on the outcome of OHCAs. The model considers also the participation of ambulances and pedestrians attending OHCAs, but focuses mainly on police officers.

The chapter is organised in three sections. The first two sections describe the DES model and the ABS model respectively. The third joins the models from the two previous sections and describes the proposed hybrid model.

3.1 DES model

The DES model proposed here is a submodel of the complete hybrid model of Section 3.3, meaning that this model focuses only on the description of how OHCAs are modelled and how and when the training sessions for the police officers take place, but it does not describe how each police officer is a different individual nor the interactions between them. These last aspects are going to be modelled in Section 3.2 where an agent-based approach is developed.

3.1.1 Why a DES model?

There are four main reasons why a DES model is a very suitable paradigm to to describe the attendance of OHCAs by police officers;

- The events that occur in the model are of two types: OHCAs and police training sessions.

Both of them occur at specific points in time. This means that the time can be modelled discretely, so no continuous modeling of time as in SD models is required.

- The events have an impact in the state variables: Police motivation and police training levels.
- It is important to know the order in which the different events take place and the time that takes place between them. Both of these aspects influence the outcome of the model.
- The time between events follows known statistical distributions.

3.1.2 Events description

There are three type of events in our model: OHCAs, voluntary training sessions and obligatory training sessions. Next, for each of these events we are going to describe briefly the event, specify the distribution followed by the times between two events of that type and detail what happens when that event occurs.

Out-of-Hospital Cardiac Arrest

Event description:

An out-of-hospital cardiac arrest happens. One pedestrian witnesses the event and calls the emergency services, the pedestrian may or may not start the CPR and another pedestrian may go in search of an AED. At the same time an ambulance and the nearest police car are warned and they travel as fast as possible to the place. Once the first responder (police, ambulance or pedestrian) arrives, the patient is attended and survives or not depending on the time between the cardiac arrest and the CPR, the time between cardiac arrest and the defibrillation and the training level of the first responder. The survival of the patient is going to be modelled via a survival probability function depending on the previous factors.

Time between events' distribution:

We consider that the occurrence of OHCAs follows a Poisson process (Section 2.2), which an usual assumption for this kind of events (Chan, 2017). Notice that the three required properties are satisfied: 1. OHCAs occur individually in time. 2. The number of OHCAs in a period of time (a, b) is not influenced by the number of OHCAs that occurred previous to a. 3. The number of OHCAs expected in any period of time of length s remains the same when the Poisson process is used to simulate what day the OHCA occurs, because there is no evidence of a seasonal component within the year or week. However it is known that OHCAs occur more often during daytime hours than during nighttime (Wallace et al, 2013; and Schriefl, 2019), and this affects the resources available (number of ambulances and police cars, availability of public AEDs). For this reason the day of the OHCA is going to be simulated using a homogeneous Poisson process and the hour with a *day occurrence probability* and a uniform distribution within the daytime/nighttimne hours. This means that the days between two consecutive OHCAs can be computed by creating an observation of an exponential distribution $Exp(\lambda)$, where λ is going to be the number of expected OHCAs per year in the region of interest.

Event routine:

The event of an OHCA is composed of a lot of smaller events that happen either at the same time or consecutively. This complex process is represented in Figure 3.1. However, this process is a simplification because in a real OHCA some of the small events may vary or may never occur, for instance a pedestrian may never call the emergency services (112). This is why it is important to remark that we are considering only the OHCAs that are witnessed by a pedestrian who afterwards calls the 112, this way unwitnessed OHCAs or OHCAs witnessed by the police or the ambulance are not considered. Unwitnessed OHCAs normally led to the death of the patient and the survival probability does not depend on the response time. Section 3.3 includes a detailed description of all the assumptions made in the proposed hybrid model.

Bearing this in mind, when an OHCA occurs the process is the following:

1. An OHCA occurs in a public location in the region of interest.
2. A pedestrian arrives to the place of the event.
3. The pedestrian recognizes that there is an emergency and calls the 112.
4. The pedestrian "*ends*" its call with the 112. At this point three processes happen almost concurrently:
   (a) The 112 calls the nearest **ambulance** and asks for help. The ambulances are considered to be in fixed locations, i. e., they do not patrol the city. We also consider that there is always an available ambulance in the nearest ambulance station, because in each station more than one ambulances are stored.
   (b) The 112 calls the nearest **police car** and asks for help. The police cars are considered to be patrolling the city, each of them in a given patrolling region, which are data inputted to the model. The 112 calls the nearest police car, which will depend on the location of each police car in its patrolling region in that given moment of time. We consider that the nearest police car could be busy, in this case the 112 will call the second nearest car. It is considered that in each police car there are two police officers.
   (c) The 112 continues its call with the **pedestrian** and guides him/her to start the CPR. At the same time (we consider that there are more than one witnesses) the pedestrians organize themselves and send one of them to look for the nearest public AED.

- It can be assumed that the duration of the call from the 112 to the police or the ambulance and the time the pedestrians need to organize themselves and send someone to get a public AED, is the same (or very similar). This allows to consider all the times, except from the displacement times, as a single variable called: **Reaction Time**. The reaction time involves all time consuming processes except for the displacements and it is independent of who the first responder is.

5. The police and the ambulance travel from their location to the place of the OHCA. The pedestrian travels from the location of the OHCA to the nearest public AED and then back. The time they need is called *displacement time*.
6. Once the last of the three responder arrives (either police, ambulance or pedestrian) the event is finished. We wait until the last responder arrives to save the times each responder has needed and then statistically analyse the results.

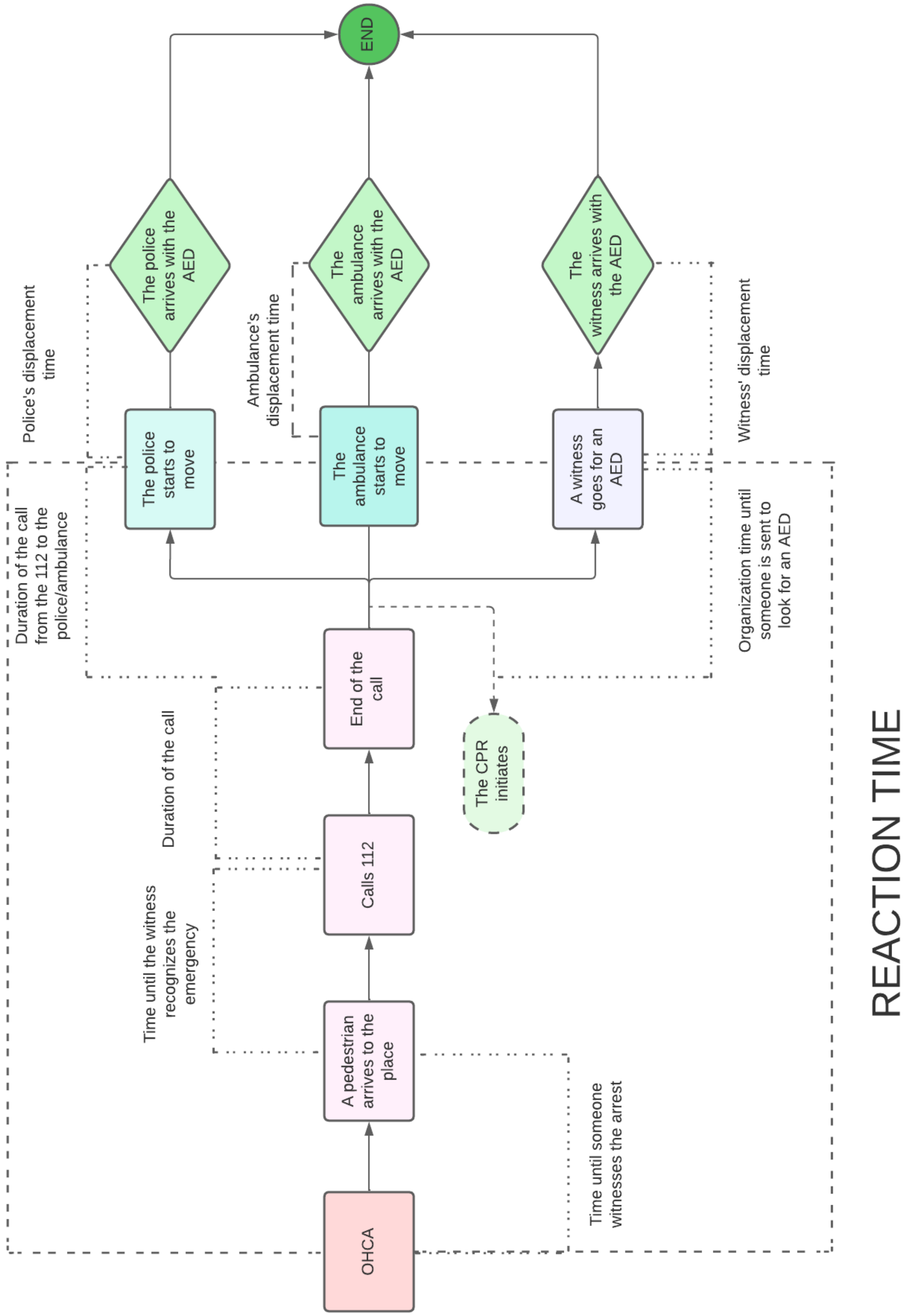


Figure 3.1: Descriptions of the events that happen when an OHCA occurs.

It is common (for instance in the city of Pamplona happens) for patrolling regions to be time-dependent. This means that during the day there are more regions than during the night. This can also happen with the available public AEDs and ambulances. Some results (Wallace et al, 2013 and Schriefl, 2019) show that OHCAs are more frequent during the day than during the night. This phenomenon is further amplified when specifically considering street OHCAs (as in this project), as the presence of people in the streets decreases significantly during nighttime. For these reasons, it is important to take into account what day and at what hour each OHCA takes place.

The simulation clock counts the time in days, so the day of the week can be obtained getting the rest of dividing the simulation clock by 7 and rounding it up, being 1: Monday, 2: Tuesday ... 7: Sunday. To simulate the exact hour, and taking into account that OHCAs happen more often during the day, first, it is simulated if the OHCA occurs during the day or during the night: to do so a probability (p_{day}, a model parameter) is considered and a random uniform number (u) is generated, if $u < p_{day}$ then the OHCA occurs during the day if not it occurs during the night. Then the exact hour of the OHCA is generated following a random uniform distribution either considering the daytime hours or the nighttime ones. Notice, that if the night represents the $0 < \delta < 1$ part of the day then p_{day} should satisfy $p_{day} > (1 - \delta)$, this way it satisfies that during the day OHCAs have a higher occurring probability than during the night. Notice that, if the number of OHCAs per year is small (one per week or less) then the probability that two OHCAs occur the same day is very low, and the day of occurrence of the OHCAs can still be modelled as an homogeneous Poisson process.

In order to simulate the OHCA event we follow these steps:

1. The OHCA location is generated uniformly at random in the area of study.
2. The reaction time x_i is generated uniformly at random. The parameters of the uniform distribution are model parameters.
3. To compute the displacements times, the following steps are followed in each case:
   (a) The police cars patrol the city. The city is considered to be divided in a finite number of patrolling sectors (which do not necessarily have to cover all the area and can overlap with each others). To simulate the position of the nearest police car, a random point is generated uniformly in each patrolling sector. Once one police car is simulated in each sector, their distances to the OHCA's location are computed using OSM. The shortest distance is returned. The police displacement time is computed using the driving speed (a model parameter). The possibility that the nearest police car may be busy and unable to attend the cardiac arrest is taken into account: let p_{oc} be the probability of the nearest car being busy, then to know if it is busy or not, a random number u is generated uniformly in the interval $(0, 1)$; if $u < p_{oc}$ then the nearest car is busy and the second nearest car is considered, else the nearest car is able to attend the OHCA. The possibility of the two nearest cars being busy is very unlikely and it is not considered.
   (b) The ambulances are considered to be placed in fixed locations in the area of interest. So, to calculate the nearest ambulance displacement time we compute, using OSM, the distance between every ambulance station and the location of the OHCA, the shortest distance is saved. Then using the driving speed (a model parameter) the ambulance displacement time is calculated.

(c) For the pedestrian, the shortest path to the nearest public AED is computed using OSM. Then the distance is duplicated and returned. With the pedestrian speed (a model parameter) the pedestrian displacement time is calculated.

4. Once the displacement times are computed, the first responder is chosen, it is the one with the lowest displacement time.

5. The lowest displacement time is used to compute the survival probability of the patient. If the first responder is the pedestrian or the ambulance, the survival probability is considered a function of the time until CPR (t) and the time until defibrillation ($s > t$). The survival function is (Valenzuela et. al., 1997):

$$p[t, s] = \frac{1}{1 + e^{-1.3614+0.3429t+0.18633s}}. \tag{3.1}$$

Notice that the higher t and s the lower the probability the patient survives. If the first responder is the police then the survival probability function (p^*) takes into account the training level of the police officer that attend the OHCA and the function becomes:

$$en[t, s] = \frac{1}{0.25} \log \left(\frac{\frac{-0.3}{e^{-1.3614+0.3429t+0.18633s}} + \sqrt{\left(\frac{0.3}{e^{-1.3614+0.3429t+0.18633s}}\right)^2 + 5.2}}{2.6} \right), \tag{3.2}$$

$$p^*[t, s, NFE] = \frac{1}{1 + e^{-1.3614+0.3429t+0.18633s+en[t,s](NFE-0.5)}}, \tag{3.3}$$

where NFE is the effective training level of the police officer. The explanation of how this function is computed is detailed in Section 3.2.4. The training level used is the maximum of the effective training levels of the two police officers that attend the OHCA, we consider that the most experienced one leads the CPR and the defibrillation.

6. Once the survival probability (sp) is computed. a random number (u) is generated following a random distribution in the range (0,1). If $u < sp$ the patient survives, else the patient dies. This is considered the outcome of the OHCA and modifies the police agents' motivation following the algorithm explained in section 3.2.5.

Now we will study the survival probability function proposed by Valenzuela et. al. (1997). The function $p[t, s]$ is a function from $[0, \infty) \times [0, \infty) \to [0, 1]$, where $s > t$. It is a strictly decreasing, continuous function, that satisfies $lim_{t\to\infty} p[t, s] = 0$ and $lim_{s\to\infty} p[t, s] = 0$, this is, if the time until the CPR or the defibrillation is too big the patient dies. Figure 3.2 represents function $p[t, s]$ for different value of t and s, notice that it has been considered that s is at least $t + 1$, i. e., there is at least one minute of CPR before the defibrillation. It can also be verified that after 10 minutes if no CPR has started the patient is almost sure dead: $p[10, 11] = 0.0160285$.

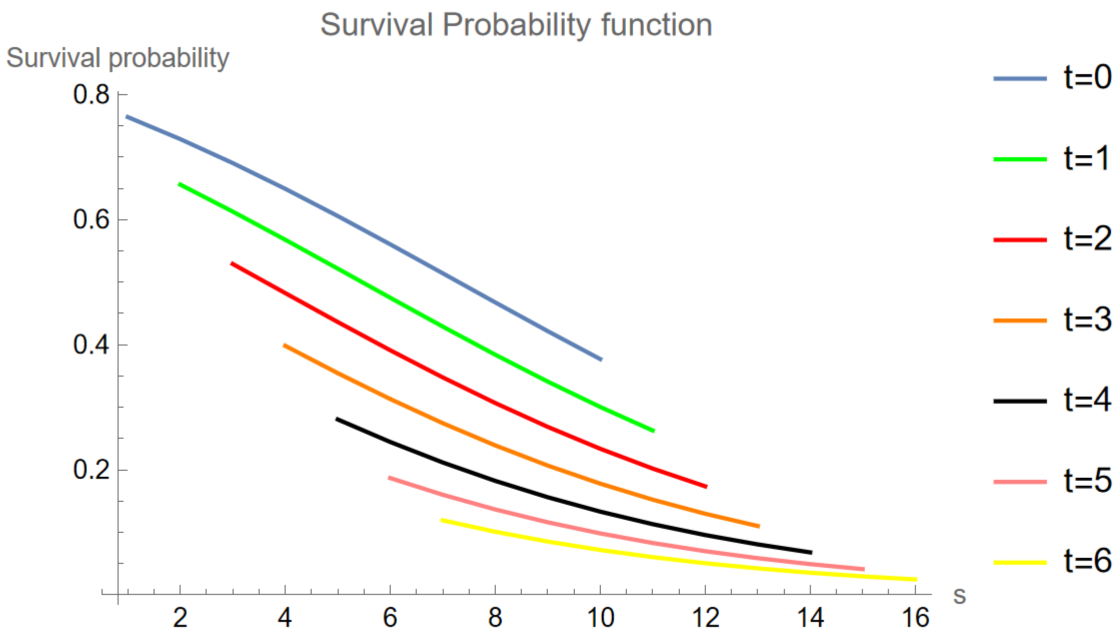


Figure 3.2: Original survival probability function. (Valenzuela et. al., 1997). t is time until CPR and s time until defibrillation.

We do not consider the training level of the emergency services (ambulance) nor of the pedestrians in the survival function, because the model does not consider these responders as individual agents, so we can assume that the their training level is always the mean training level (0.5), in that case both survival probability functions (p and p^*) are equal.

Notice, that the model could still work if no pedestrians or even no ambulances are considered, this is, it is possible to only analyse the behaviour of the police regardless of the rest of possible first responders. It could that the pedestrian who witnesses the OHCA calls the 112 but never attempts the CPR, in this case the first public service to arrive, either ambulance or the police, starts the CPR at the arrival time. Here, the recommended duration of the CPR is between 1 and 3 minutes (American Heart Association, 2020), after that the defibrillation should be attempted (if needed). This second possible scenario is also considered in the hybrid model developed. In this case, the CPR time is going to be generated with a uniform distribution, whose extremes are two model parameters.

Voluntary Training Session

Event description:

When this events occurs a voluntary training session takes places. Each police officer decides whether or not to attend the session depending on their motivation, if they are motivated enough they will go. In the session, professional emergency personnel will teach the police officers how to do a CPR, how to use AEDs and other basic life support techniques that could be useful when attending an OHCA.

Time between events' distribution:

We are going to consider that voluntary training sessions take place in regular time intervals. This is, they take place every VT days, for instance, once each month or once a year. Considering the timing of a training session as a deterministic rather than stochastic factor is a justifiable and realistic assumption. This is because the decision of when to conduct a training session is typically made by humans, indicating a deliberate choice rather than a random or uncertain event.

Event routine:

1. The police officers with a motivation greater than a given threshold Ψ are selected.
2. The police officers selected increase their training level according to what is explained in Section 3.2.3
3. The moment of the next voluntary training session is computed and the events list is updated.

Obligatory Training Session

Event description:

When this event occurs an obligatory training session takes places. Every police officer has to attend this training session. Usually they take place with a lower frequency than the voluntary training sessions. In the session professional emergency personnel will teach the police officers how to do a CPR, how to use AEDs and other basic life support techniques that could be useful when attending an OHCA.

Time between events' distribution:

We are going to consider that obligatory training sessions take place in regular time intervals, for the same reasons as the voluntary training sessions. This is, they take place every OT days, for instance, once each month or once a year.

Event routine:

1. All the police officers increase their training level according to what is explained in Section 3.2.3
2. The moment of the next obligatory training session is computed and the events list is updated.

Table 3.4 summarizes all the parameters of the DES submodel including a brief description of each one.

3.1.3 Modelling car police speed from real data

When developing the DES model one of the main problems we have encountered has been how to estimate the value of the parameters of the model. Particularly we focused on the mean velocity of the police cars. The aim is to develop a procedure that allows to estimate this parameter knowing posterior information of the OHCAs that have been attended. The problem can be defined as follows

Knowing the real time a police officer has needed to attend an OHCA and the exact location of the OHCA (information that is usually available in the health services databases), the objective is to estimate the mean speed of the police cars. It is considered that the total time (T_i) a police officer has needed to attend the OHCA, can be split into two parts: the reaction time x_i and the displacement time d_i/v. The reaction time comprehends all the time consuming processes except for the car displacement, this is, the call to the emergency services (112), the start up of the police car and the time needed, once the police has arrived to the place of the OHCA, to find the patient and start the defibrillation. It is considered that the reaction time depends on each particular OHCA and that it follows an unknown probability distribution. The displacement time d_i/v, depends on the distance between the OHCA location and the police officer location (d_i) and the mean speed of the police car v. Naturally, in each arrest, the distance between the police and the cardiac arrest d_i is different and unknown with the data available; however, it is considered that all the police cars have the same mean speed v, which is the parameter we want to estimate.

If the reaction time is measured in minutes, the distance in kilometers and the speed in kilometers per hour; the total (time in minutes) is equal to:

$$T_i = x_i + 60\frac{d_i}{v}.$$

Let N be the number of total times T_i known (i. e. the number of data instances available), and therefore the number of cardiac arrest locations known. To estimate the mean velocity of the police cars, we generate for each of the N cardiac arrest available, K possible locations of the police officers, uniformly distributed in the studied region, then the distances from each police location to the location of the cardiac arrest are computed using OSM. This way the distances d_{ij} with $i = 1, ..., N$ and $j = 1, ..., K$ are obtained, this is, for each cardiac arrest there are K candidates to distance at which the police officer could originally have been.

We propose the following iterative algorithm to estimate the speed. In the first iteration $l = 1$ the following optimization problem with restrictions is solved

$$\begin{aligned} \min_{x_i, v} \sum_{i=1}^{N} \sum_{j=1}^{K} \left(T_i - \left(x_i + 60\frac{d_{ij}}{v} \right) \right)^2 . \\ 0 \leq x_i \leq bound_t \\ 0 \leq v \leq bound_v \end{aligned} \tag{3.4}$$

The minimization algorithm used to solve the previous problem (Equation 3.4) is SLSQP (Sequential Least Squares for Quadratic Problems), an algorithm especially designed to solve quadratic optimization problems with restrictions.

Let $x_i^{(l)}$, $v^{(l)}$ be the reaction times and the speed estimated in the lth iteration. In the iteration $l + 1$ the errors of the previous iteration $e_{ij}^{(l)}$ are computed using the following formula

$$e_{ij}^{(l)} = \left| T_i - (x_i^{(l)} + 60\frac{d_{ij}}{v^{(l)}}) \right|.$$

Once the errors are calculated, for each arrest an elitist kernel $E()$ is applied to the corresponding errors. This means that for each arrest the distances d_i that have had the greatest error are removed (considered with weight 0 in the summatory of Equation 3.4), this is because those distances represent the locations with the lower probability of the police officer having been there. To do this removal, in each iteration the percentile 0.9^{l-1} of the errors (considering each arrest separately) is computed and all distances with an error (computed with the results of the previous iteration) greater than the percentile are removed. So, in each iteration $l > 1$ the optimization problem becomes

$$\begin{aligned} \min_{x_i, v} \sum_{i=1}^{N} \sum_{j=1}^{K} E\left(\left(T_i - \left(x_i + 60\frac{d_{ij}}{v}\right)\right)^2\right). \\ 0 \leq x_i \leq bound_t \\ 0 \leq v \leq bound_v \end{aligned} \tag{3.5}$$

Notice that it is exactly the same problem as in (Equation 3.4) but considering a lower number of possible distances for each arrest.

The iterative process continues until only one distance is left for each arrest, or until the percentile is lower than a given tolerance (this tolerance depends con the order of N, normally it is 10^{-3}). This second stopping criteria is necessary because it is possible that for a given arrest two or more distances converge to same error, and then it is not possible to choose which of them has to be removed.

It is really important to establish an upper bound to the speed in the optimization problem (Equation 3.4)-(Equation 3.5) if we want the proposed algorithm to work. This is a realistic assumption, because the speed of a police car is limited by numerous factors such as the traffic, the legal speed limit and the technical capabilities of the car. From a mathematical point of view, if no upper bound is imposed to the velocity nor to the reaction times, there is a trivial solution to the optimization problem (Equation 3.4)-(Equation 3.5), which is $v = \infty$ and $x_i = T_i$, in this case, the variability of the different distances is cancelled because the velocity is infinitely large, so the term d_i/v equals 0, and the term x_i (the reaction time) gets all the information of the total time so that all the terms in the summatory become equal to 0. This is why it is compulsory to establish an upper bound to v.

However, it is also necessary to upper bound the reaction time. If no upper bound is imposed, the solution $v = bound_v$ and

$$x_i = \frac{1}{K} \sum_{j=1}^{K} T_i - 60\frac{d_{ij}}{bound_v}$$

is, in most cases, the optimal. This is not a desirable solution, because it does not take into account the differences between distances. This solution chooses the largest speed possible so that the variance of the displacement times (d_i/v) is minimized and then only adjusts the reaction times, which is the mean between the total time and the displacement time for all the distances considered. This is not desirable because the objective is to estimate the speed.

An elitist kernel is used because with other kernels the algorithm does not achieve the desired convergence. If instead of using the elitist kernel we simply weight each distance with the size of its error compared to the total errors for that arrest:

$$w_{ij} = \frac{e_{ij}}{\sum_{j=1}^{K} e_{ij}}. \tag{3.6}$$

The problem arises when K is big enough, this is, when a sufficiently large number of distances are simulated for each arrest, which is, on the other hand, necessary to get a good estimation; then the denominator in (Equation 3.6) is much larger than the numerator for any distance j. As a consequence the variance of the weights of the different distances is very small, this means that the distances with lower errors do not get a significantly bigger weight than the ones with greater errors and, because of this, the algorithm is not able to converge.

A geometric kernel could also be used: the errors are ordered from lower to greater (for each arrest) and each distance is weighted with a weight of α^o $(0 < \alpha < 1)$, where o is the position of the distance in the list of ordered errors. This way the distance with the lowest error receives a weight of α, the distance with the second lowest error has a weight of α^2 and so on. With this kernel the algorithm converges, however it has a big bias, because two distances with similar errors can end up with very different weights.

Another option is to use a Gaussian kernel, with mean 0 and calculating the errors without the absolute value. In this case the weight of each distance is the value of the pdf (probability density function) of a normal distribution, with mean 0 and standard deviation σ, evaluated in the error of that distance. The pdf of a normal distribution with mean 0 is

$$\frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x}{\sigma}\right)^2}.$$

The main difficulty when using this kernel is to determine the value of σ. If the standard deviation is too small all distances have weights near to 0 and the algorithm does not converge, if σ is too big there is no discrimination between distances with big errors and distances with small errors. One could argue that using a σ which depends on the standard deviations of the errors of the distances for each arrest could solve the problem, however, some experiments that have been conducted have shown that the standard deviation of the errors is usually too small compared to the magnitude of the errors, so this means that the standard deviation would need to be scaled, which again leads us to same problem. Theoretically an optimal σ could be found that discriminates correctly the distances, however, this optimal σ would depend on model parameters such as K and N. The elitist kernel, on the other hand, does not depend on any parameters and is slow paced (because it uses percentiles) which allows the algorithm to reach good results.

One question that could be asked is why does the algorithm not estimate the reaction times distribution parameters in addition to the mean speed? The main problem of estimating both parameters is that the available information is very small compared to the general variability of the data, this means that there is not enough information to accurately estimate both of them. In fact, the reaction times that the algorithm estimates act as error accumulators, i. e., they store the variability between the different arrests and the errors committed because of not knowing the real distance at which the police officer really was, allowing the algorithm to estimate correctly the mean speed.

To analyze the performance of the algorithm artifitial data has been generated: we have generated N cardiac arrest locations uniformly distributed in the studied region (the Spanish city of Pamplona) and for each of those we have randomly generated (following a uniform distribution) the location of a police car. Then a reaction time has been generated in each case, following a uniform distribution in a given interval. Finally, the total time has been calculated, using OSM to estimate the distance from the police car to the arrest and using a given speed. The speed used has been the same in all the cardiac arrests, whereas the reaction time varies in each arrest. Then, once the total times and the location of each cardiac arrest have been saved (which are the available data), for each arrest 100 possible police locations have been generated (following a uniform distribution) and their distances to the cardiac arrest location have been computed and saved.

Once the data has been generated, we applied the algorithm, Table 3.1 shows the results for different scenarios. The first column shows the real speed with which the data had been generated, the second the lower and upper bounds of the uniform distribution used to generate the reaction times, the third column shows the number of cardiac arrests considered, the fourth the upper bound used for the speed in the algorithm, the fifth the upper bound used for the reaction time in the algorithm, the sixth the initial speed considered, the seventh the initial reaction times considered (we have considered them the same in all the arrests), the last column shows the speed estimated by the algorithm. From the results we can extract the following conclusions:

- The algorithm estimates with a reasonable error the mean speed of the police cars
- The error tend to lower when the number of cardiac arrests considered increases, but the execution time of the algorithm also increases because of the quadratic minimization algorithm used in each step.
- Although it can not be seen in the table, the algorithm is robust to different initial values of the speed and the reaction times.

Real velocity	Reaction time	Nº Arrests	Bound_v	Bound_t	$v^{(l)}$	$x_i^{(0)}$	estimated_v
10	(30,90)	40	100	180	30	120	10.2044
10	(30,90)	120	100	180	30	120	10.18699
10	(30,90)	400	100	180	30	120	10.03627
25	(30,120)	40	100	180	50	120	27.95681
25	(30,120)	120	100	180	50	120	25.89799
30	(30,135)	40	100	180	50	120	30.84255
30	(30,135)	120	100	180	50	120	30.98896
60	(30,150)	40	100	180	50	120	64.26971
60	(30,150)	120	100	180	50	120	64.202316

Table 3.1: Results of the algorithm used to estimate the speed of the police cars. The first two columns show the actual speed and reaction time interval of the attending police car for OHCAs, the third column represents the number of simulated OHCAs, and the fourth and fifth columns indicate the bounds used in equations 3.4 and 3.5. Columns 6 and 7 display the algorithm's initial speed and reaction time, and the last column presents the estimated speed.

Once the speed of the police cars has been estimated one could try to recover the reaction time for each arrest. To do so the results of the elitist kernel could be used, to recover the distance at which it is more probable that the police officer actually was (d^*_{ij}) and then recover the reaction times using the estimated speed

$$x_i = T_i - 60\frac{d^*_{ij}}{v_{est}}.$$

However, this is not possible, because the distances d^*_{iuj} are not an accurate estimation of the real distances at which the police car really was. Figure 3.3 show the differences between the estimated distances and the real distances. One can see that the differences are significant, being even greater than 4 km. Nevertheless, this errors are normally distributed around the 0 and this allows the algorithm to correctly estimate the mean speed, although the real distances are not recovered. Figure 3.3 has been generated using real speed of 10 km/h and 40 cardiac arrests.

Lastly, it could be thought that a better way to generate the possible locations of the police cars would be to generate them following a mesh instead of uniformly at random. Generating the locations following a regular mesh means that the region of interest is divided into equally spaced points and each of those points is considered a possible location for the police car. The advantage of this method is that, if the spatial discretization is sharp enough, it can be assured that one location near the real location is going to be included into the possible locations, as a consequence the probability that a good estimate of the real distance is recovered by the algorithm increases. However, empirical results (not included) show that: on one hand, for it to exist a significant difference between the random generation and the mesh generation, the mesh must be really sharp and then the computational cost is too high; on the other hand, even if a location near to the real one is generated, the lack of available data makes the algorithm unable to find the real distance in most cases.

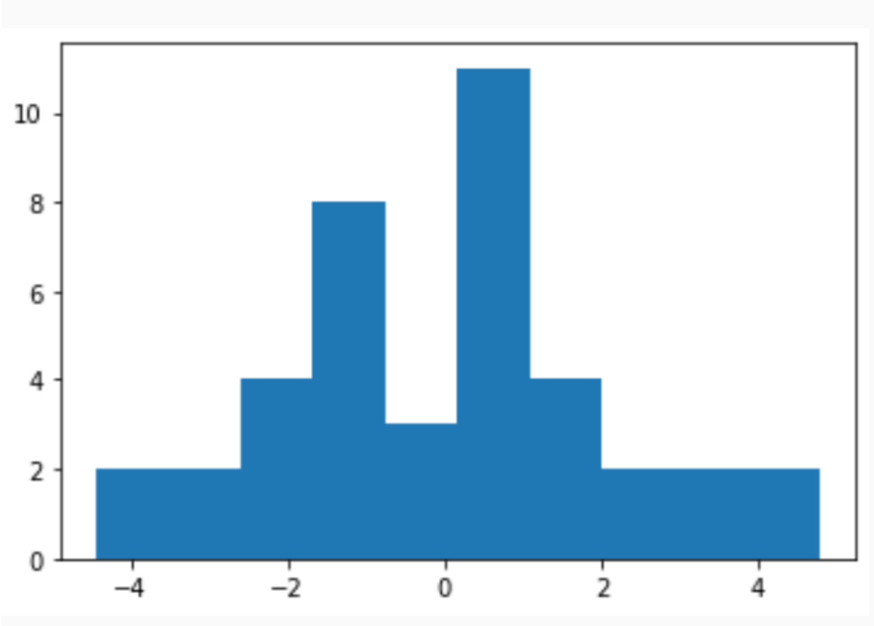


Figure 3.3: Differences between the real distances and the estimated ones

3.2 ABS model

In this section we are going develop an innovative Agent Based Simulation (AB) model to describe police officers that attend OHCAs. This ABS model completes the DES model proposed in Section 3.1 giving rise to the hybrid model of Section 3.3. The aim of this ABS model is to allow an individual description of each police officer and a different evolution in time of each of them, due to different personal characteristics, different interaction with other agents, different experiences with the OHCAs and different attendance to the training lessons (Section 3.1). This individualization will allow in Section 3.3 to analyze the impact of the police training sessions on the outcome of the OHCAs, in terms of patient survival probability.

3.2.1 Why an ABS model?

To answer the question of why is an ABS model suitable to model the system we are studying, we are going to follow the questions proposed by Macal (2018) in Table 2.1.

Model Purpose / Value added of Agent-based Modeling

What specific problem is the model being developed to address?

The problem addressed is to calculate the benefit that equipping the local police with AEDs and programming training CPR sessions has on OHCAs outcomes.

What specific questions should the model answer?

The model should answer the following two questions:

1. In the cases where the police are the first responders, how much does the patient's survival probability increase? compared to if the patient had been attended by an ambulance or a pedestrian.

2. How do the police training programs on CPR and defibrillation, specially their frequency, affect the outcome of the OHCAs?

What kind of information should the model provide to help make or support a decision?

The model should provide information of the gain in survival probability of the patients due to the intervention of the police as first responders and the gain in patients' survival probability of the different training programs considered.

Why might agent-based modeling be a desirable approach?, What value-added does agent-based modeling bring to the problem that other modeling approaches cannot bring?

The hybrid model combines a DES model with a ABS model. ABMS is used because the outcome of an OHCA depends greatly on the training level of the first responder (Weiss et. al., 2018) that is why it is important to consider each police officer as a different individual with a different training level which changes dynamically over time, this is not possible with a DES or a SD model.

All About Agents

Who should be the agents in the model?

The main agents of the model are going to be the police officers, who are the decision makers.

Other agents that will interact with the police officers are the ambulances and the pedestrians, these will be considered as part of the environment because they lack individual behaviour.

Who are the decision makers in the system?

The decision makers of the system are the police officers.

What are the entities that have behaviors?

The police officers are the only agents with behaviours.

Where might the data come from, especially for agent behaviors?

The data for agent behaviour will come from the outcomes of the OHCAs and from the training sessions.

Agent Data

What data on agents are simply descriptive (static attributes)?

The name, the age, the susceptibility and the learning rate are static attributes of the police agents.

What agent attributes are calculated endogenously by the model and updated for the agents (dynamic attributes)?

The dynamic attributes are the absolute and effective training level and the motivation.

What is the agents' environment?

The agent's environment is the city and the OHCAs and training sessions that take place in it. We also include the ambulances and pedestrians who respond to OHCAs as part of the environment.

How do the agents interact with the environment?

Agents interact with the environment by attending OHCAs as first responders and by attending training sessions. The outcome of the OHCAs modifies their motivation and attending training sessions increases their training level. At the same time the outcome of an OHCA depends on the training level of the police acting as first responder. In addition, attending an OHCA allows the police officer to remember what has been learned in the training sessions.

Is agent mobility in space an important consideration?

Agent mobility is a vital aspect, because the agent location in the environment will determine how much time will take the police officer to attend the OHCA, which is the main influential factor in patient's survival probability (OHCA's outcome).

Agent Behaviour

What agent behaviours are of interest? What decisions do the agents make and what information is required to make such decisions? What behaviors are being acted upon? What actions are being taken by the agents?

Each agent has two behaviours of interest. First, depending on the level of motivation of the agent it will decide whether or not to attend voluntary training sessions. Second, the age and the learning rate of the agent will determine how much the agents learns in each training lesson and how fast he or she forgets what he or she has learned.

In addition, agents' performance quality when attending an OHCA will depend on their training level.

How would we represent the agent behaviors? By If-Then rules? By adaptive probabilities, such as in reinforcement learning? By explicit heuristics? By regression models or neural networks?

Agents decision whether or not to attend a voluntary training lesson will be modelled using an if-then rule. Agents knowledge acquisition and loss will be modelled using mathematical functions.

Agent Interactions

How do the agents interact with each other?

Agents interact with each other through a network of contacts. The interactions consists of telling the other agents the outcome of an OHCA the police has attended, this leads to a change in agents' motivations.

How expansive or focused are agent interactions?

Agent interactions are quite expansive, although the influence of an agent over the others decays as the distance between them in the network gets bigger.

<u>Agent State</u>

What are the states the agents could find themselves in at some point in time, in the model?

The state of each agent is defined by his or her motivation and training level.

Under what conditions do agent states change?

Agent change states when attending an OHCA or training lesson.

<u>Agent Recap</u>

How do we design a set of experiments to explore the importance of uncertain behaviors, data and parameters?

We are going to consider a base scenario, with the information of the police sectors, ambulance stations and public AEDs locations of the Spanish city of Pamplona. The rest of the model parameters are going to be chosen following literature results and the frequency of the training sessions is going to follow the AHA recommendations, one obligatory session every two years. Then an alternative scenario adding more frequent voluntary sessions is going to be studied.

How might we validate the model, especially the agent behaviors and the agent interaction mechanisms?

To validate the displacement times of the ambulances and police cars, real data from the health services of the city of Pamplona are going to be used. In order to validate and calibrate the rest of model we will estimate the values of the fixed parameters based on an extensive research in the literature and for the rest of parameters an analysis of alternative scenarios will be conducted.

In addition, the model will be presented to and discussed with local police officers (of the city of Pamplona) who usually carry AEDs and with Extra-Hospitalary Emergency personnel who are in charged of the police training sessions.

3.2.2 Agent definition

In this section we are going to describe how the agents of the model are defined. Some of these aspects have already been answered in the Section 3.2.1, however here they will be explained in a greater detail. As it has already been said, the agents of the model are the police officers, they are the only elements of the system with an individual and modular characterization. Other responders (pedestrians and ambulances) lack individual behaviour, therefore they will be considered a part of the police officers' environment. The agent definition process is divided into four parts: first, the attributes of the agents are described, this attributes describe the agent's state and determine the agent's behaviour; second, how the attributes are initialized in the model is explained; third, a detailed description of the agents' environment is given; finally, the interactions between agents and between agents and their environment is explained.

Attributes

Each police officer is defined by twelve (or ten) attributes. Seven (or five) of them are constant, which means that they do not change over time. The other five attributes are variable, i. e., they change during the simulation depending on how the agent interacts with other agents and the environment. The attributes that are variable are the ones that define the state of the agent in each moment of time. Table 3.2 summarizes the attributes of a police agent, specifying the notation used for each attribute and whether it is constant or variable. In the following we will explain each attribute separately and explain how they change over time.

Attribute	Notation	Type
Name	"Police_nº"	Constant
Learning rate	α	Constant
Initial Training Level	ITL	Constant
Continuous Training Duration	CTD	Constant
Continuous Training Frequency	CTF	Constant
Age	ϵ	Constant
Susceptibility	σ	Constant
Motivation	μ	Variable
Absolute Training Level	NFA	Variable
Effective Training Level	NFE	Variable
Last Recall	UR	Variable (Auxiliary)
Refresh parameter	γ	Variable (Auxiliary)

Table 3.2: Attributes of a police officer

Name

The name is a string that identifies unequivocally each agent. Each police officer has its own and unique identifier and it can no change over time.

Learning rate

The learning rate is a parameter that determines how much does a police officer learn from a training lesson. It represents the ratio of knowledge acquired, in a training session, out of the

Participants	Never	More than 2 years ago	Less than 2 years ago
390	77	142	171

Table 3.3: Answers to the question: When did you receive your last CPR training session? in an interview made to the local police in Asturias (Spain). Angulo-Menéndez and Pérez (2017).

total amount of knowledge not yet known. It takes its values in the interval $(0, 1)$; 0 is excluded because it would mean that the agent can not learn and 1 is excluded because it would mean that the agent is a perfect learner. The exact mechanism of how the learning rate interacts and modifies the absolute training level is explained in Section 3.2.3.

Initial Training Level

The initial formation level represents how much training had the police officer received before the start of the simulation. We consider that there are three possibilities: $ITL = 0$, meaning that the police officer had never attended a training session before; $ITL = 1$, meaning that the police officer had received a training lesson but a lot of time ago and he/she has almost forgotten everything; and $ITL = 2$, meaning that has been attending training sessions regularly over the past years or months.

This classification is inspired in a study made by Angulo-Menéndez and Pérez (2017), where they interviewed police officers in the Spanish community of Asturias and asked them about their training level in CPR, the results are reproduced in Table 3.3. There we can see that police officers may be divided into three groups (not necessarily with the 2 years threshold), officers with no experience, officers with some experience and officers with high experience.

Continuous Training Duration and Continuous Training Frequency

These parameters only make sense if $ITL = 2$, because it is the only case where the agent has been receiving training sessions on a continuous basis over time. The Continuous Training Duration represents how many years has the police officer been receiving training sessions in a regular basis and the Continuous Training Frequency represents how frequent where those training sessions. The CTD is given in years and the CTF in months. if $ITL \neq 2$ these parameters are not considered. Naturally, $CTD > CTF$.

Age

The age of the police officer is a important parameter to consider, because several studies (Cho and Kim, 2021; Wilson et al., 1983) have discovered that the younger subject is (police officer, doctor, nurse...) the slower he/she forgets what has been learned in a CPR and defibrillation training session. How the knowledge is acquired in training sessions and lost over time and the influence of the age in this process is explained in detail in Section 3.2.3. Because of some particular reason explained in Section 3.2.3 the age needs to be considered in the range $[2.25, 4.5]$. If we assume that the police officers' age range between 18 and 65 years, then function $fAge$ (Equation 3.7) allows to convert the real age into a value in the interval $[2.25, 4.5]$. $fAge$ is the line passing through the points $(18, 2.25)$ and $(65, 4.5)$.

$$fAge[\epsilon] = \frac{2.25}{47}(\epsilon - 18) - 2.25. \tag{3.7}$$

Susceptibility

When an event, like an OHCA, occurs, it affects the people who where involved. Naturally, it affects the patient and his/her family, but it also has an impact in the responders. This impact however, depends on each particular person, this is, two people could witness the same event but receive different impressions. To measure how attending (or witnessing) an OHCA affects the agents' motivation differently each agent has its own susceptibility. This parameters ranges between 0 and 1 and the way it changes the impact of an OHCA outcome in the agents' motivation is described in Section 3.2.5.

Motivation

As it has been already explained in Section 3.1.2, the motivation is a parameter that determines the willingness of a police officer to a attend a voluntary training session. The motivation is a parameter that ranges in the interval $(0, 1]$ and changes in time according to what is explained in Section 3.2.5. The motivation of an agent increases if he/she attends an OHCA and the patient survives, if he/she witnesses an OHCA where the patient survives or if one of his/her workmates attends an OHCA where the patient survives. Likewise if the patient dies their motivation decreases.

Absolute Training Level and Effective Training Level

Because of how is modelled the knowledge acquisition and loss (Section 3.2.3) two parameters are necessary to represent the training level. The Absolute Training Level (NFA) is a slow changing variable which represents the knowledge the agent had at the end of the last training session he/she attended. The NFA changes only when the police officer goes to a voluntary or obligatory training session, how this change takes place is explained in the corresponding section. The NFA takes values in the interval $(0, 1)$, because the knowledge is measured over 1, this is, 1 represents the maximum level of knowledge attainable.

The knowledge is lost over time (Murre et al, 2013; Adekola et al, 2013; Ruth et al., 1984), so when a police officer attends an OHCA the training level used to compute the survival probability of the patient is not the NFA. The effective training level of a police officer at a given moment of time is a value $NFE \in (0, 1)$ smaller than NFA, which is computed using the NFA and a knowledge loss function (which depends on the age of the agent and the time since the officer last remembered how to do a CPR), this function is described in Section 3.2.3. The NFE takes a different value in each moment of time.

Last Recall

The Last Recall is an auxiliary parameter that represents the last time the police officer remembered how to do a CPR and a defibrillation. This parameter is essential to compute NFE using the knowledge loss function (Section 3.2.3). This parameter takes real values ($UR \in (-\infty, \infty)$). If $UR = 0$ it means that the last time the agent remembered was at the beginning of the simulation, a negative value means that the last remember occurred before the start of the simulation. If UR equals the simulation clock, then $NFA = NFE$, this means that the agents has just attended a training session and remembers everything he/she has learned.

Refresh parameter

The refresh parameter (γ) is an auxiliary parameter used to model the amount of knowledge an agent recovers when attending an OHCA. γ changes its values according to what is explained in Section 3.2.3 and always values in the interval (NFE, NFA).

Attributes initial distribution

When initializing the model, it is necessary to give a value to each of the attributes of each police officer. This is why, it is important to define how these initial values are going to be established. For each parameter we are going to allow three options: either the value is established manually, randomly or fixed. When the value of a parameter is set manually, it means that a value for that parameter is inputted (in the model's initial configuration) for each police officer individually, this is, if there are 5 police officers and the parameters α is manual, then 5 α values must be specified in the model's initial configuration, one for each agent. When the value of a parameter is fixed, then only one value for that parameter is specified and all the agents take this same value, this is, if α is fixed with a value of 0.4 then all the agents will have $\alpha = 0.4$. When the value of the parameter is established randomly, then the user specifies the parameters of the random distribution, from which the values of the parameter are going to be extracted, this is, if the value of α is decided randomly from a uniform distribution (a, b), then the parameters a and b are inputted in the model's initial configuration and for each police agent his/her α is extracted randomly from a uniform distribution in the interval (a, b). Next, we will explain the initial distribution of each attribute.

Name

The name can be set either manually or "randomly". A manual setting would require for the user to indicate the name of each police officer in the model. For this parameter there is, actually, no random setting, but rather an automatic setting, which means that each police officer receives the name "Police_i" where i goes from 0 to the number of officers-1. This parameter does not allow a fixed setting because it has to be different for each agent.

Learning rate

The learning rate admits the three setting options: either manual, fixed or "random". In the manual and fixed options the values must be in the interval $(0, 1)$. If the random option is chosen there are two options: either a uniform distribution or a beta distribution. In the uniform distribution the upper and lower extremes of the uniform distribution must be specified, resulting in an interval $(a, b) \subset (0, 1)$. In the beta distribution the values of α_b and β_b must be set.

The use of a uniform distribution is only supported by the fact that it is a bounded distribution which gives random values in the wanted interval and does not preponderate some values over others. However, some results Angulo-Menéndez and Pérez (2017) and Broomfield (1996) give an insight into what could the real distribution of α be. As α represents how much knowledge does an agent acquire in a training session, table 3 (T1 from now on) from Angulo-Menéndez and Pérez (2017) and table 5 (T2 from now on) from Broomfield (1996) can be used to estimate this parameter: T1 provides information of the mean and standard deviation of the score that some participants achieve after a CPR training session and T2 provides information of the score that 19 nurses got before and just after a CPR training session. From both of these tables important information to estimate the learning rate's distribution can be obtained.

From T1 we can estimate the mean (0.78675) and the standard deviation (0.04984) of the distribution of the learning rates. Knowing the mean and the standard deviation one could think of adjusting a normal distribution, however, then it could not be assured that the generated α values would stay in the desired interval $(0, 1)$, on the other hand a beta distribution is bounded and so it could be more accurate. Knowing that the mean of a beta distribution (with parameters α_b and β_b) is equal to $\frac{\alpha_b}{\alpha_b+\beta_b}$ and that its variance is $\frac{\alpha_b\beta_b}{(\alpha_b+\beta_b)^2(\alpha_b+\beta_b+1)}$, with the values obtained in T1, a system of equations can be defined and solved (numerically) giving $\alpha_b = 1.86163$ and $\beta_b = 0.504597$. Now, T2 provides information to estimate 19 instances of α values. Because we know the score before and after the test, how much knowledge has acquired each nurse during the training session can be estimated (see Section 3.2.3 to understand how knowledge acquisition is modelled). For instance, if the score in the first test is 2/8 and in the second test is 6/8 the estimated α is 4/6, because 2/8+4/6*6/8=6/8, this is the nurse has learned 4/6ths of the knowledge he/she did not know before the training session. This 19 estimations can be plotted in a histogram with the proposed beta distribution, the result can be seen in Figure 3.4, it is quite accurate. Notice that the model allows any other values for the parameters of the beta distribution, however, the proposed values are highly recommended.

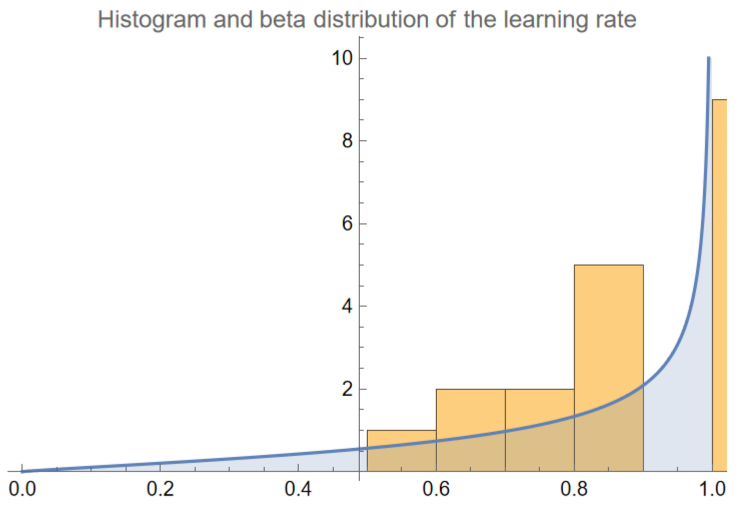


Figure 3.4: Estimation of the distribution of the learning rate.

Initial Training Level

The Initial Training Level admits a manual, fixed or random setting. If the training level is fixed then either all the agents have no experience or medium experience or high experience. If the training level is random then a discrete probability distribution is defined for the three possible ITL values, this is, three probabilities are given one for each ITL value (0,1,2), they must sum up to 1. Then each generated agent gets an ITL value according to this distribution.

Continuous Training Duration and Continuous Training Frequency

Both of these values are only considered if the ITL value of the considered agent is 2. Both of them can be set manually, randomly or fixed. If a random distribution is used to generate the ITL values then the fixed and the random CTD and CTF values are only applied to the agents that satisfy $ITL = 2$. For both of them the random setting implies a uniform distribution, whose intervals must be defined. Naturally, CTD and CTF must always be chosen so that they satisfy $CTD > CTF$, this is, the frequency can not be bigger than the duration.

Age

this parameter allows random, fixed and manual setting. The random setting is made by means of a uniform distribution, whose parameters have to be inputted. The values this parameter must be always in the interval $(2.25, 4.5)$.

Susceptibility and Motivation

Both of these parameters allow random, fixed and manual setting. The random setting in both cases is made by means of a uniform distribution, whose parameters have to be inputted. The values of both parameters must always be in the interval $(0, 1)$.

Absolute Training Level

The initial value of the NFA depends on the value of the ITL. If $ITL = 0$ then the police officer has never attended a training session and, therefore, his/her initial training level (both absolute and effective) are 0. If $ITL = 1$ then it means that the last training session the police officer attended was long ago, therefore the agent will have forgotten almost everything that he/she has learned. Assuming that the agent had learned α (his/her learning rate) and bearing in mind that the knowledge loss function asymptotically decays to 0.4 (Section 3.2.3) then the initial NFA of the agent will be $= 0.4\alpha$. This means that the agent can only remember 40% of what he/she learned so long ago.

If $ITL = 2$ then it is assumed that the police officer has been attending training session for the last CTD years with a frequency of a session every CTF months. Knowing this information the previous CTD years can be simulated only considering that the agent has attended training sessions every CTF months and applying the knowledge acquisition and loss process of Section 3.2.3, the initial NFA and UR can be computed.

Effective Training Level

Because the NFE is a function of NFA, UR, α and ϵ, the initial value of NFE can be computed using the ones of the other four parameters, following what is explained in Section

3.2.3.

Last Recall

As the Last Recall is an auxiliary parameter that relates the NFA with the NFE, its initial value depends intrinsically on NFA's initial value, which again depends on the Initial Training Level of the agent. If $ITL = 0$, then $UR = -\infty$, meaning that the police officer had never received a training session. If $ITL = 1$, then $UR = -2$ (years), 2 is an arbitrary number inspired in Table 3.3, but because of how the knowledge loss function (Section 3.2.3) is constructed and the fact that $ITL = 1$ means that the last training session the agent attended was a long time ago, then any number much bigger than 6 months could be acceptable. If $ITL = 2$, then the process followed to get the initial NFA also returns the last time the agent remembered.

Refresh parameter

The refresh parameter (γ) is always initialized to the same value as the NFA, because we do not consider that the agents have attended OHCAs before the start of the simulation.

Environment

The agents' environment is formed by 6 elements:

- **The city**: the city where the simulation takes place defines the spatial position of the agents and defines the paths the police cars, ambulances and pedestrians follow to attend an OHCA. The traffic in the city also conditions the movement speed of the police cars and ambulances. Other elements of the city that affect the simulation are: the patrolling sectors of the agents and the location of the public AEDs. It is important to notice that the city is not time-invariant, i. e., the traffic, the available public AEDs and the patrolling sectors may depend on the time of the day considered.
- **The OHCAs**: Are the main event in the model. All the agents attributes and parameters are related to the OHCAs. Agents attend training sessions so that they can attend the OHCAs in a better way.
- **The ambulances**: Are one of the main elements in the agents' environment. The ambulances also try to attend the OHCAs as fast as possible.
- **The pedestrians**: Are a fundamental element in the OHCA event. They witness the OHCA and call the 112, also they start the CPR (in most of the cases). They also try to get an AED and attend the OHCA as fast as possible.
- **The training sessions**: Both voluntary and obligatory training sessions represent the part of the environment where the agents improve their skills and abilities.
- **The police officers' network of contacts**: This network defines how each agent is connected to the other agents. an edge in the contact network (in this context) means that if an agent attends an OHCA he/she will tell his/her neighbours about the outcome of that OHCA. This is, an edge between two agents represents the existence of an exchange of experiences between them.

The environment is modelled and simulated mainly via the DES submodel. This submodel governs when the OHCAs and the training sessions happened and which agents take part in each of them.

The only environment element that is not described by the DES model is the contact network. This network is part of the ABS submodel. This network is generated randomly following a Erdös-Rényi algorithm (Algorithm 2.4.1) where the probability is an inputted parameter to the model. We impose that there are no isolated vertices (vertices with 0 degree) because each police officer knows at least another one, the one he/she patrols with. To do so if after the Erdös-Rényi algorithm there are any isolated vertices, then each of these vertices is tried to be reconnected with the rest of the vertices with the given probability, until all isolated vertices get a connection.

Interactions

The agents' interactions can be divided into two categories: interaction between agents and interactions with the environment.

The interaction between agents takes place when an agent attends an OHCA and tells the outcome to his/her workmates. This affects the agents' motivation to attend voluntary training sessions. The contacts network is a fundamental element in this process. How this motivation in propagated is explained in Section 3.2.5.

The interaction with the environment takes place mainly through the OHCA event (Section 3.1.2). There the police officer is located in a specific place in the city and moves through it to attend an OHCA, at the same time the nearest ambulance and pedestrian also attempt to attend it. The police training level affects the survival probability of the patient and the outcome of the OHCA affects the agent's motivation. Another interaction agent-environment is trough the training lessons, there the agents increase their training levels (absolute and relative).

3.2.3 Modelling knowledge acquisition and loss

In this section it is explained how do agents acquire knowledge during the training sessions and how they lose it if they spend time without putting it into practice. First, how the knowledge loss function is modelled is explained. Second, we will detail the relationship between the NFA and NFE attributes through the knowledge loss function, the age, the UR and γ. Finally, we will model how does the NFA change in a training lesson, this is how knowledge is acquired.

Some previous research studies (Fan et. al., 2016) have shown that police officers can be trained to effectively use AEDs. Other studies (Cho and Kim, 2021) have demonstrated that repeating training sessions over time helps to retain CPR knowledge and achieve better results in practice. Angulo-Menéndez and Pérez (2017) showed that it exists a correlation between the periodicity with which police agents attend training sessions and their CPR knowledge. The agents that have been trained more recently are the ones with higher knowledge and willingness to perform a CPR. Everett-Thomas et al. (2016) also showed that there is a direct relationship between knowledge, CPR performance and patient survival. However, there are evidences (Weaver et al., 1979) that the CPR techniques can usually not be learned completely with just one training lesson, this means that if an agent attends a training session he/she will not acquire 100% of the knowledge taught.

According to Cho and Kim (2021) a standard 180 minutes training session consists of: 30 minutes of theory, 90 minutes of compression practices (usually with a mannequin), 30 minutes of ventilation practices (also with a mannequin) and 30 minutes of AED practices. Sometimes training sessions without ventilation practices are also conducted, they last 150 minutes. The quality criteria (Kleinman et al., 2015) for a CPR are: compression rate of 100-120 compressions per minute, compression depth of 50-60 mm, hand position in the middle of the sternum and recoil of 100%. Cho and Kim (2021) concluded that training sessions without ventilation practice benefit knowledge retention and that younger students retain more information than the older ones.

The AHA (American Heart Association) recommends retraining every 2 years after the first training to maintain the educational effect of the CPR (Kleinman et al., 2015). However, some studies (Cho and Kim, 2021; Adekola et. al., 2013; Broomfield, 1996) show that the acquired knowledge is lost within a period of 3 to 6 months. Moser and Coleman (1992) showed that the retention of CPR skills start to decay 2-4 weeks after the training. Weaver et. al. (1979) also showed a significant deterioration of CPR skills 6 months after the training session, however the participants that had reviewed CPR related information within the 6 months after the initial training achieved better results. Everett-Thomas et al. (2016) also discovered a substantial deterioration in CPR skills after 3 months unless there was a frequent use of those skills. Because of all these results, the retraining frequency should be reduced from 2 years (AHA suggestion) to 6 months. In addition, one interesting fact (Adekola et. al., 2013) is that practical CPR skills are forgotten faster than theoretical knowledge. However, to simplify the model we are not going to distinguish between practical and theoretical skills.

Wilson et. al. (1983) showed in their study that even in well-trained individuals, CPR skills deteriorate by 40% after one year. In addition, they discover that there was no significant difference between the skills deterioration after 1 year and after 2 years. They propose that the skill retention function reaches its limit (40%) after one year and then it stabilizes. In practice this means that any agent will always remember at least 40% of what he/she has learned.

Taking into account the above results, we look for a knowledge loss function, $R(\Delta t)$, that verifies:

- $R : [0, \infty) \to [0, 1]$
- Continuous, smooth (C^∞) and strictly decreasing
- $R(0) \approx 1$. Just after the training session the agent must remember almost everything he/she has learned. Which does not necessarily mean that the agent has acquired all the possible knowledge.
- $\lim_{\Delta t \to \infty} R(\Delta t) = 0.4$. Any agent will always remember at least 40% of what he/she has learned.
- $R(3) << 1$. After 3 month there is a significant deterioration in the agent's CPR skills.
- $R(\varepsilon) \approx 1$, with ε small. If there is a frequent use of the skill or frequent training then there is a very low loss of skill. This is, during the first month since the last training or

use of the skill there is a good skill retention.

where Δt is the time, in months, since the last training session the agent attended. Because we need a function that has a slow decay at first and then rapidly decreases until 0.4 is reached, a sigmoid function ($\frac{1}{1+e^{-x}}$) is proposed:

$$R(\Delta t) = -0.6\frac{1}{1+e^{-3\Delta t+b}} + 1.$$

Coefficient 3 is arbitrary and has been chosen for convenience. The value of the coefficient b can be fixed using the tables 2 and 3 from Cho and Kim (2021). These tables show the mean score obtained by police officers in Korea right after CPR training (table 2) and 3 months after (table 3), four quality indicator were measured: accuracy of compression rate, accuracy of compression depth, accuracy of recoil and accuracy of compression position. Dividing the score obtained in each indicator after three months between the score obtained right after the training and averaging the results of the four indicators an estimation of the skills retention after three months can be obtained. This estimation is 65%, this is we expect that after 3 month without training or practicing, an agent remembers 65% of the knowledge he/she has acquired. Mathematically this means that we impose the condition $R(3) = 0.65$, this is a simple equation that can be easily solved and it is obtained that $b = 8.6635$. Notice that it is impossible to adjust a value for b such that $R(0) = 1$ not even if coefficient 3 is considered an adjustable parameter. Then, the knowledge loss function is:

$$R(\Delta t) = -0.6\frac{1}{1+e^{-3\Delta t+8.6635}} + 1.$$

This function is continuous, of class C^∞ and strictly decreasing. $R(3) = 0.65 < 1$ and $\lim_{\Delta t\to\infty} R(\Delta t) = 0.4$. Finally, $R(0) = 0.999896$ which is not exactly 1 but it is enough close for practical purposes.

Some of the previously mentioned studies show that the age is a factor that influences the skills retention capacity of an agent. More precisely the younger the agent is the longer he/she can retain the acquired knowledge. However, there is not available data to know how does the knowledge loss function change with the agent's age. For this reason we have estimated the effect of age assuming that the youngest agents retain 65% of their knowledge 4 month after the training and the oldest ones retain 65% of it 2 months after. This is, the oldest agents take 2 months to forget 35% of their CPR knowledge while the youngest take 4 months. To model this assumptions there are two options either the coefficient 3 of $R(\Delta t)$ is modified or the coefficient b. Changing coefficient b means translating the function while changing coefficient 3 means changing the function's slope. We have decided to modify the slope so this way the fact that the younger agents forget slower than the older ones is better represented. Leaving 3 as a free parameter and imposing that $R(4) = 0.65$ we get that the function for the youngest agents is $R(\Delta t) = -0.6\frac{1}{1+e^{-2.25\Delta t+8.6635}} + 1$. In the same way, imposing $R(2) = 0.65$ we get that the function for the oldest agents is $R(\Delta t) = -0.6\frac{1}{1+e^{-4.5\Delta t+8.6635}} + 1$. This is the reason why in Section 3.2.2 we asked the agent's age to be in the range $[2.25, 4.5]$. So, finally the knowledge loss function used in the model is

$$R(\Delta t) = -0.6\frac{1}{1+e^{-\epsilon\Delta t+8.6635}}+1 \quad (3.8)$$

where ϵ is the agent's age. Figure 3.5 displays Function (3.8) with ages 2.25, 3 and 4.5.

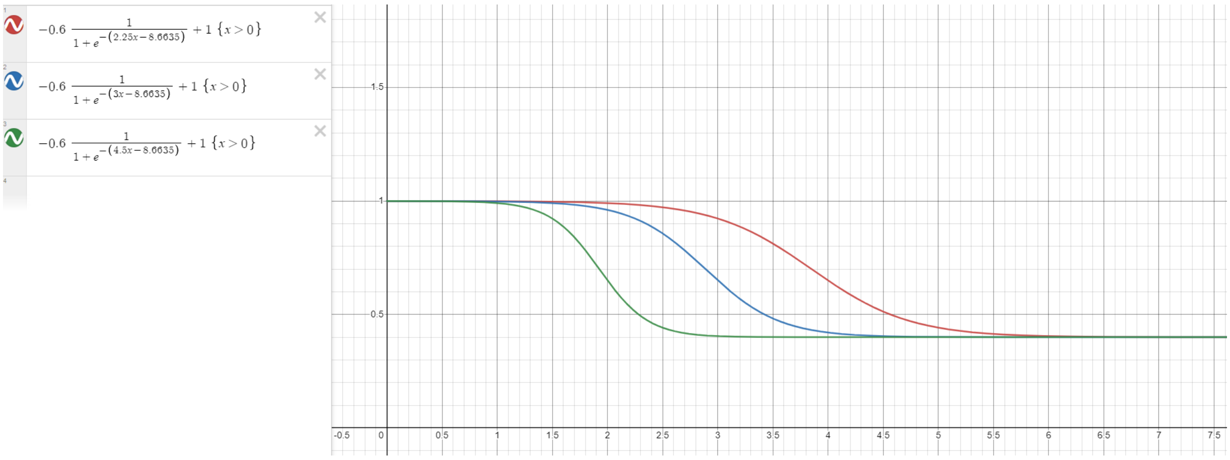


Figure 3.5: Knowledge loss functions

Now, once the knowledge loss function is defined, the relationship between the absolute training level (NFA) and the effective training level (NFE) is going to be explained. To do so it is important to remember that the learning rate (α) represents the percentage (in a (0,1) range) of knowledge an agent acquires in a training session out of the total knowledge (which is measured in a (0,1) range) the agent did not know before of the session. This is, the first time an agent participates in a training session, his/her training level is α, because he/she has learned 100α % of the total unknown knowledge, which initially is 1. It is also important to remember that UR is the last time the agent attended a CPR and defibrillation training session or put into practice CPR and defibrillation related skills.

The effective training level (NFE) is the real training level an agent has at a given moment of time τ. The NFE is defined as

$$NFE = NFA * R(\tau - UR)$$

where, naturally, $\tau - UR = \Delta t$, which is is the time, in months, since the last training session the agent attended or the last time CPR and defibrillation related skills were put into practice. So, the effective training level is the absolute training level modified by the knowledge loss function of the agent. This definition of the NFE satisfies that just after a training session $NFE \approx NFA$, because $R(0) \approx 1$, and if $\Delta t >> 0$ then $NFE \approx 0.4NFA$, because $lim_{\Delta t \to \infty} R(\Delta t) = 0.4$.

Next, we want to model the fact that whenever an agent attends an OHCA then the agent refreshes/recovers part of the knowledge he/she has lost, this makes it necessary to redefine the NFE. We are going to ask this knowledge recovery process to satisfy some conditions:

1. If a police agent has not attended an OHCA since the last training session he/she took part in, then the NFE must be modelled following $NFE = NFA * R(\tau - UR)$, this is, if there is no knowledge recovery the knowledge loss process is the one previously defined.

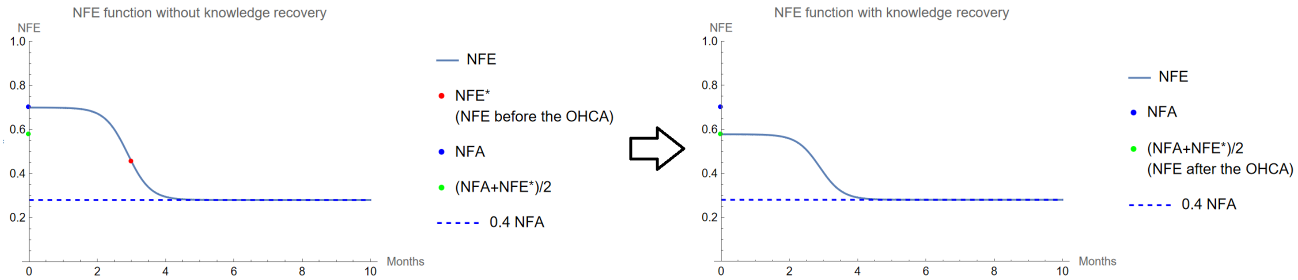


Figure 3.6: Knowledge recovery process when an OHCA occurs

2. No new knowledge can be acquired just by putting into practice the knowledge acquired in the training sessions, this is, the NFA can not be incremented by an OHCA event and the NFE can never be greater than the NFA.
3. The limit of the NFE when $\Delta t \to \infty$ must still be $0.4NFA$, this is, the agent will always remember 40% of what he/she has learned in the training sessions.
4. Whenever an agent recovers knowledge the knowledge loss function restarts, i. e., $\Delta t = 0$, but with a lower maximum point. This means that just after attending an OHCA the agent does not remember everything, i. e. $NFE \neq NFA$ but recovers half of the lost knowledge, i. e. $NFE = \frac{NFA+NFE^*}{2}$, where NFE^* is the agent's effective training level at the time of the OHCA.

All of these conditions essentially mean, that when an OHCA occurs the NFE function is modified, the agent recovers the knowledge partly and the forget process restarts. This process is shown in Figure 3.6, notice that the effective training level (red dot in the left image) increases after attending the OHCA (green dot in the right image).

To model this process we propose the NFE to be

$$\frac{aNFA + b\gamma}{a+b}R(\Delta t) + \left(0.4 - \frac{0.4a}{a+b}\right)(NFA - \gamma)$$

where a and b are real numbers. γ is an auxiliary agent's parameter that takes the value NFA after every training session and changes to NFE (to compute this NFE the previous γ value of the agent is used) when the agent attends an OHCA. Condition 1 is satisfied directly, because if $\gamma = NFA$ then $NFE = NFA * R(\Delta t)$; condition 3 is also satisfied, because $\forall a, b \in \mathbb{R}$ $\lim_{\Delta t \to \infty} NFE = 0.4NFA$. Notice that if condition 4 is satisfied then condition 2 is satisfied too. To satisfy condition 4 we impose that when $\Delta t = 0$ then $NFE = 0.5NFA + 0.5\gamma$, this is, $NFE = 0.5NFA + 0.5NFE^*$. It is is easy to prove that this will happen if and only if $5a = b$, so we choose $a = 1$ and $b = 5$. Finally, the relationship between NFE and NFA, at a given simulation time τ, is given by

$$NFE = \frac{NFA + 5\gamma}{6}R(\tau - UR) + (0.4 - \frac{1}{15})(NFA - \gamma)$$

where γ is an auxiliary agent's parameter that takes the value NFA after every training session and changes to NFE (to compute this NFE the previous γ value of the agent is used) when the agent attends an OHCA. Whenever the agent participates in a training session or attends an OHCA his/her UR is set equal to the simulation clock (after the NFA and γ update).

Finally, when an agent attends a training session (either voluntary or obligatory) his/her NFA is modified following the rule:

$$NFA = NFE + (1 - NFE)\alpha.$$

This is, the new absolute training level is equal to the training level of the agent at that moment of time (NFE) plus how much the agent learns (α) from what he/she does not know ($1 - NFE$). When an agent attends an OHCA his/her NFA is not modified.

Notice that the proposed knowledge loss function does not exactly follow the exponential decay suggested by Murre et al. (2013), however by using a sigmoid function we assure an exponential behavior after 3 months and before that there is a slower decay, which is coherent with the findings of Stickgold et al., (2000). Stickgold et al., (2000) found that in cases of high consolidation rates there may be a temporary increase in recall probability, after that it will stabilize and exponentially decay.

3.2.4 Modelling the influence of training level in survival probability

In this section, we start from the original survival probability function (Equation 3.1) and we modify it to take into account the training level of the police officer who attends the cardiac arrest. This new function is only going to be used when the first responder is a police officer, because they are only agents of the model with a modelled training level.

Before including the training level in the survival probability function it is necessary to do a small literature review, to understand how does the training level of the first responders influence survival:

The most critical factor in patient survival of OHCA is the time from collapse until the start of treatment. In general, the survival of an OHCA is less than 10% (Axelsson et al., 2012). The efficacy of OHCA resuscitation can be maximized when EMS maintain competency in the skills and knowledge of resuscitation (Soar et al., 2010). If the quality of CPR is poor, survival rates decreased. Effective resuscitation involves the delivery of evidence-based knowledge and skills that require learning, mastery, and deliberate practice (Cheng et al., 2018).

Dyson et al. (2014) reviewed the influence of EMS practitioners experience and exposure to OHCAs on patient survival. The association between the volume of cases and the outcome of OHCA patients was uncertain. The average annual exposure to OHCA by EMS practitioners was reported to be between 4 and 9 cases per year. The conclusion of the review was that there was no clear evidence that EMS practitioner career experience or exposure to OHCA cases or advanced life support procedures was associated with survival or procedural performance. However, the overall quality of the 11 studies considered was low.

Another systematic review, conducted by Bray et al. (2020), found no association between practitioners with longer careers and patient outcomes, but on the other hand, it found a positive relationship between OCHA exposure (number of OHCAs attended) and patient outcome. Dyson et al. (2016) found that higher team exposure in the preceding three years was associated with increased survival to hospital discharge (STHD): compared to a median of $\leq$6 exposures, >6-11 exposures =**OR (Odd Ratio) 1.26 (95% CI: 1.04-1.54)**, 11-17 exposures =**OR 1.29 (95% CI: 1.04-1.59)**, >17 exposures = **OR 1.50 (95% CI: 1.22-1.86)**. Dyson et al. (2016) also found lower survival to discharge in patients treated by teams who have not been exposed to OHCA in the preceding 6-months **(OR 0.70, 95% CI: 0.54-0.91**) compared to those with recent exposure (<1 month). Tuttle and Hubble (2018) found that higher exposure of the treating paramedics was associated with increased ROSC (Return of Spontaneous Circulation). When compared to the <15 exposure reference group, those with <15 exposures had an **OR of 1.22 (95% CI 1.11-1.36)**.

Talikowska et al. (2015) conducted a systematic review to study the influence of correct performed CPR on the patient survival probability. Notice that correct CPR performance can be associated with a high training level. It was found that chest compression depth (recommended between 50 mm and 60 mm by the European Resuscitation Council (ERC)) was significantly associated with STHD and ROSC. Compression rate (recommended between 100-120 per minute) was associated with STHD and, within that range, a lower rate is recommended (nearer to 100 cpm) due to a correlation found between higher compression rate and lower compression depth. Idris et al. (2015) found that lower compression rate (80-99 cpm) was associated with lower STHD, taking 100-119 cpm as reference, (**OR 0.73, 95% CI: 0.57-0.93**) and higher compression rate (120-130 cpm) was also associated with lower STHD (**OR 0.63, 95% CI: 0.45-0.88**).

Weiss et al. (2018) studied two groups of paramedics: a less experienced group (who participated in less than 10 OHCAs during the previous year) and a more experienced group (who participated in 10 or more OHCAs during the previous year). The results of the article showed that the less experienced group had a ROSC rate of 22.2% while the more experienced achieved 28.9% and differences were significant between the two groups. (p-value = 0.047), **RR 1.30 (95% CI 1.001, 1.692)**. There was not a clear linear relationship between number of OHCAs resuscitations and the sustained ROSC rate. The data suggests that there may be a threshold of approximately 10 OHCAs. So paramedics no meeting a minimum of 10 annual OHCA should undergo supplementary training.

In view of the results of the literature, it is clear that although years of work experience do not increase the probability of patient survival, having attended more OHCAs does. In the end, this is what matters, since more years of working experience does not necessarily imply more training in CPR and defibrillation, but having attended more OHCAs does generally imply a better training level. On the other hand, most of the results (Bray et al., 2020; Talikowska et al., 2015; Weiss et al., 2018) seem coincide in that the survival probability of a patient attended by an agent with a high training level increases by 30% with respect to a patient attended by an agent with a low level of training. Most of the odds ratios were close to 1.3 if they were taking low training level as the reference class or 0.7 if they were taking high training level as reference.

Therefore, the survival probability function $p^*[t, s, NFE]$ should satisfy:

1. $p^*[t, s, 0.5] = p[t, s]$ $\forall t, s \in \mathbb{R}^+$ with $s > t$. This is, if the effective training level of the agent is the mean one (i. e., $NFE = 0.5$) then both functions coincide. The original survival probability function was calculated without taking into account the training level of the first responders so it is reasonable to think that this is equal to assume average training level for all the responders.
2. Assuming that low training level is represented by $NFE = 0.25$ and high training level by $NFE = 0.75$, then p^* should satisfy that $1.3p^*[t, s, 0.25] = p^*[t, s, 0.75]$ $\forall t, s \in \mathbb{R}^+$ with

$s > t$.

where t is the time until CPR, s is the time until defibrillation and $p[t, s]$ the original survival function proposed by Valenzuela et. al. (1997).

We consider a simple modification of the original function:

$$p^*[t, s, NFE] = \frac{1}{1 + e^{-1.3614+0.3429t+0.18633s+en(NFE-0.5)}} \tag{3.9}$$

It is trivial to see that Function (3.9) satisfies condition 1. To make Function (3.9) satisfy condition 2, the coefficient en must be adjusted:

For clarification purposes we take $x \equiv -1.3614 + 0.3429t + 0.18633s$, then

$$\begin{aligned}
1.3\frac{1}{1 + e^x e^{en(-0.25)}} &= \frac{1}{1 + e^x e^{en(0.25)}} \\
\iff 1.3(1 + e^x e^{0.25en}) &= 1 + e^x e^{-0.25en} \\
\iff 1.3 + 1.3e^x e^{0.25en} &= 1 + e^x e^{-0.25en} \\
\iff 0.3 &= e^x(e^{-0.25en} - 1.3e^{0.25en}) \\
\iff \frac{0.3}{e^x} &= \frac{1}{e^{0.25en}} - 1.3e^{0.25en} \qquad .
\end{aligned}$$

To simplify the equation we do the following change of notation:

$$z \equiv e^{0.25n}.$$

Multiplying the equation by z we get a second grade equation:

$$\frac{0.3}{e^x} = \frac{1}{z} - 1.3z \iff 1.3z^2 + \frac{0.3}{e^x}z - 1 = 0.$$

Solving the second grade equation:

$$e^{0.25en} = z = \frac{-\frac{0.3}{e^x} \pm \sqrt{\left(\frac{0.3}{e^x}\right)^2 + 4 * 1.3}}{2.6} \iff en = \frac{1}{0.25}\log\left(\frac{\frac{-0.3}{e^x} + \sqrt{\left(\frac{0.3}{e^x}\right)^2 + 5.2}}{2.6}\right)$$

Recovering the original value of x, we get that en is a function of t and s:

$$en[t, s] = \frac{1}{0.25}\log\left(\frac{\frac{-0.3}{e^{-1.3614+0.3429t+0.18633s}} + \sqrt{\left(\frac{0.3}{e^{-1.3614+0.3429t+0.18633s}}\right)^2 + 5.2}}{2.6}\right).$$

Finally, the new survival probability function is

$$p^*[t, s, NFE] = \frac{1}{1 + e^{-1.3614+0.3429t+0.18633s+en[t,s](NFE-0.5)}}. \tag{3.10}$$

3.2.5 Modelling the propagation of motivation between police officers

In this section we are going to explain how the outcome of an OHCA affects the motivation of the police officers that have attended it and how this variation in their motivation propagates to the rest of agents. When a police officer attends an OHCA as the first responder the outcome of the OHCA affects his/her motivation: if the patient survives the OHCA, the agent understands that his/her role in the resuscitation has been useful and has helped to save a life therefore his/her motivation to learn more increases; however if the patient dies, the motivation of the agents decreases, he/she does not see the point on getting trained if they can not save lives. As not every person reacts the same way to the same event, we consider that each agent has a different susceptibility (σ) which measures how much does the outcome of the OHCA affect the agent's motivation. We also take into account that not all the OHCAs are the same and some of them may be more impressive than others. The impact of the OHCA is going to be called feedback, because it is the feedback the agent receives from his implication in the arrest resuscitation; the feedback is going to be denoted by φ and takes values in the interval $(0, 2)$ following an uniform distribution. If the patient has survived: $\varphi \in (1, \varphi_s)$, if not: $\varphi \in (\varphi_i, 1)$, where φ_s and φ_i are model parameters. If the police that has attended the OHCA has a motivation of μ before the OHCA, after the OHCA his/her motivation becomes μ^*:

$$\mu^* = (1 - \sigma)\mu + \sigma \max(\mu * \varphi, 1).$$

It can be assured that $\mu^* \in [0, 1]$. Notice that the new motivation is a convex linear combination of the old motivation and the one modified by the feedback, where the combination parameter is the susceptibility. We also consider that when a police officer attends an OHCA as first responder then the officer tells his/her experience to his/her workmates. Notice that each OHCA is attended by two officers, so both of them will tell their respective workmates the outcome of the OHCA, notice also that both of these agents must be adjacent in the contact network because they work together. When the feedback has been positive (i. e. the patient has survived) the experience told is positive and the workmates also experiment an increase in their motivation. However, the same happens if there are bad news, this is, if the patient has died, the workmates will also experience a decrease in their motivation. In addition to the feedback and the susceptibility of each agent there is another element to consider when deciding how this news affect the workmates, this third element is the distance to the officer that was the first responder. This reflects the fact that if an agents hears the news directly from an agent that attended the OHCA the impact of the news is much bigger than if he/she hears the news from a police agent who is a friend from the one that was first responder. To compute the distances between agents the network of contacts is used and to model the fact that the further away, the lower the impact of the news a new parameter called network fatigue ($\xi \in (0, 1)$) is defined. The propagation algorithm for the feedback among the police agents is defined bellow: the main idea is that in each iteration (i) a new feedback ($\varphi_{effective}$) is computed, which is $\varphi - |1 - \varphi| * \xi * i$ (if $\varphi > 1$) or $\varphi + |1 - \varphi| * \xi * i$ (if $\varphi < 1$), and the agents that are at a distance i from the agent that attended the OHCA update their motivations following $\mu^* = (1 - \sigma)\mu + \sigma \max(\mu * \varphi_{effective}, 1)$, where $\varphi_{effective}$ is the feedback computed in that iteration.

We also consider that if the first responder is the ambulance (emergency services) or a pedestrian and the patient survives, then there is a (lighter) increase in the motivation of the police officers that attend the cardiac arrest. Even though the officers have not arrived first to the location of the OHCA (are not the first responders), they witness that CPR and defibrillation are effective because the patient has survived, and so their motivation to learn more increases. However, we consider that if the patient dies, there is no change in the agents' motivations because they were not the first responders, so there was no direct implication. Because of the fact that the police agents were not the first responders in this case, we consider that there is no propagation of the motivation among the rest of the agents. If the patient survives, the agent's motivation is updated in the same way as before, but the feedback takes its values in a narrower interval.

To end this section, we will explain the feedback propagation algorithm. But, before detailing it, it is necessary no specify (or remember) some useful notation:

- Feedback: φ
- Network fatigue: ξ
- Number of police officers: N
- Police officers that attend the OHCA: $0, 1$ (whithout loss of generality)
- Motivation of the q-th police officer: μ_q
- Susceptibility of the q-th police officer: σ_q
- Diameter of the network of contacts: δ
- Adjacency Matrix of the network of contacts: A
- List of Considered Police Officers: LCP

Propagation algorithm

1)$\mu_k^* = (1-\sigma_k)\mu_k + \sigma_k \max(\mu_k * \varphi, 1)$, $k = 0, 1$(*update the motivation of the polices that attended the OHCA*)

2) LCP=[j for j in range(0,$N-1$)].remove(k), $k = 0, 1$ (*list of all police officers expect the ones that attended the OHCA*)

3) From i=1 to δ:

    $\varphi_{abs} = |1 - \varphi|$

    variation=ξ*i

    variation=max(variation,1)

    If $\varphi > 1$: (*there is an increase in motivation*)

        $\varphi_{effective}$=φ-φ_{abs}*variation

    If $\varphi < 1$: (*there is a decrease in motivation*)

        $\varphi_{effective}$=φ+φ_{abs}*variation

For j in LCP:

If $A[0,j]=1$ *or* $A[1,j]=$: (*police officers at distance i from police* 0 *or* 1)

$\mu_j = (1-\sigma_j)\mu_j + \sigma_j \max(\mu_j * \varphi_{effective}, 1)$ (*Update motivation of police at distance i*)

Remove police j from LCP

$A = A \times A$ (*Update adjacency matrix adding an additional distance*)

If variation=1: **Break** (*the motivation no longer changes*)

End of algorithm

3.3 The proposed hybrid simulation model

Real-world systems, like the one being studied in this project, are highly complex and involve many factors, situations, and specific circumstances that cannot be fully described by a model alone. That's why mathematical models serve as simplifications of these real systems. To make the study more manageable, certain assumptions have been made in this project regarding OHCAs attended by police officers. These assumptions are:

1. The **population density** is assumed constant in the studied area. The OHCAs are generated randomly following an uniform distribution in the region of interest. This is a simplification, as more densely populated areas are more likely to experience cardiac arrest.
2. **Homogeneity in the patients** is considered, this is, no individual characteristics of the patients such as gender or age are taken into account. This is a simplification, because personal traits, such as the age, influence patient's survival probability (Pleskot, 2011).
3. Only **witnessed OHCAs** by pedestrians are considered. This excludes unwitnessed OHCAs, OHCAs that do not take place in a public place (for instance home OHCAs) and OHCAs witnessed by police or emergency services.
4. The **pedestrian** always **calls the 112**.
5. We do **not** consider cases when the **emergency was not an OHCA**. This is, the possibility of the pedestrian misdiagnosing as an OHCA something that is not an OHCA is not considered.
6. We also consider that there is **always an available ambulance in the nearest location**, because we assume that in each ambulance station more than one ambulance is stored.
7. Firefighters, helicopters, no emergency medical services (such as health center staff or paramedics) and any **other different potential first responders are not considered**.
8. It is assumed that the **patient always needs defibrillation**. It is important to bear in mind that there are different types of OHCAs and not all of them require defibrillation (Herlitz, 2008).
9. It is assumed that the occurrence of OHCAs follows a stationary Poisson process.

Once the assumptions have been cleared, we are going to explain the proposed hybrid model. This model combines the DES submodel of Section 3.1 with the ABS submodel of Section 3.2. The functioning of both models and the interaction between them has already been explained in the previous sections. Figure 3.7 shows a diagram of the hybrid model, the upper part represents the events (blue rectangles) of the DES submodel and the lower the attributes (green rhombuses) of the police agents. Light green rhombuses represent constant attributes and the darker green ones represent attributes that vary in time, rhombuses with dashed contour represent auxiliary attributes. The arrows between events and attributes represent how they influence each other: yellow arrows represent agents' attributes that affect the outcome of an event, orange arrows represent events that modify agents' attributes and green arrows represent that a constant or auxiliary attribute is involved in the modification of a variable attribute. For instance, the susceptibility influences how the outcome of an OHCA modifies the agent's motivation.

The events happen in time following their respective distributions, i. e. the OHCAs follow a Poisson process and the training sessions occur every $VT|OT$ days. If a voluntary training session coincides in time with a obligatory one, then only the obligatory training session takes place. It is not possible for an OHCA to coincide with a training session, because we assume that each police officer attends the training session outside of their patrol hours. The attributes of the police officers change whenever an event occurs, even the NFE, which is an attribute that changes continuously in time due to the knowledge loss function, is only updated whenever an event takes place.

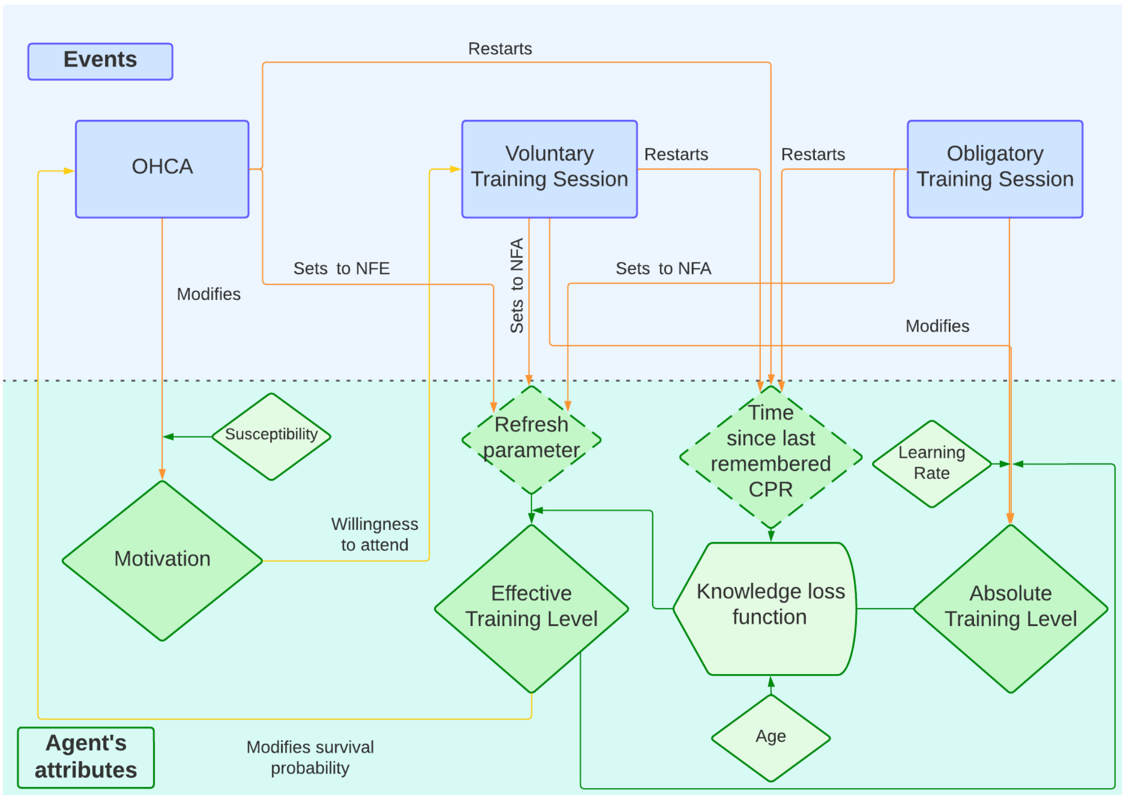


Figure 3.7: The hybrid DES-ABS model

Simulation starts with the simulation clock set at 0 and ends when the simulation clock reaches a given finalization time, which is a model parameter. The hybrid model contains a substantial number of parameters, which can be categorized into three groups: **general**, **DES** related and **ABS** related. General parameters are the ones related to real word aspects, such as the number of days in a year or the daytime hours; general input data, such as the probability that an OHCA occurs during the daytime hours; and general simulation parameters, such as the number of years to simulate or the city limits. DES parameters involve every aspect related to the DES submodel, such as the number of OHCAs in a year (which determines the frequency of the OHCAs) or the speed of the vehicles. ABS parameters involve every aspect related to the ABS submodel, such as the number of police officers considered or the network fatigue, this parameters also involve all the agents' attributes initialization parameters described in Section 3.2.2. One particularly interesting parameter is the speed of the vehicles, if just a mean speed is given then the traffic is not taken into account, that is why the model admits a list of car's speeds accompanied with the correspondent time intervals. For instance, from 00:00 to 12 am a speed of 70 km/h, from 12 am to 3 pm a speed of 40 km/h and from 3 pm to 00:00 a speed of 60 km/h. This way the hours of the day with a higher traffic are simulated with a lower car speed and the hours with a lower traffic with a higher speed. Table 3.4 shows all the model's parameters with a brief description of each of them. The mode parameter refers to the fact (explained in Section 3.1.2) that the model can be executed in two different modes. In mode 0, the model considers the scenario where the pedestrian who witnesses the OHCA after calling 112 initiates CPR. In mode 1, the model considers the scenario where the witness does not initiate CPR, and instead, CPR is performed by either the police or the ambulance upon their arrival.

When the hybrid model is executed some values are saved so that the model's behaviour can be analyzed: number of cardiac arrest simulated, number of cardiac arrest attended by police officers, number of cardiac arrests attended by pedestrians, number of cardiac arrest attended by ambulances, number of voluntary training sessions, number of obligatory training sessions, number of patients that survived, number of patients that survived in arrests attended by police officers. The NFA, NFE and motivation are recorded for each police agent every day. The probability of survival of each patient in every OHCA is also recorded.

Parameter	**Category**	**Brief description**
Years to simulate	General	Number of years to simulate with the model
Bounding Box	General	Area of the simulation, specified as min/max Latitude/Longitude
Mode	General	Mode=0: the CPR is done by the witness; mode=1: the CPR is done by the police/ambulance
Probability day	General	Probability that the OHCA occurs during daytime
Daytime hours	General	Hours that are considered daytime.
Number of arrests in a year	DES	Number of arrests in a year in the area of interest
Frequency of obligatory training sessions	DES	Days between two consecutive OTS
Frequency of voluntary training sessions	DES	Days between two consecutive VTS
Speed of the pedestrians	DES	Walking speed of the pedestrians
Speed of the vehicles	DES	List with the cars' speeds in each hour
p_{oc}	DES	Probability that the nearest police officer is occupied
Patrolling sectors of the police	DES	For each sector a list of the vertices (Lat,Long) that define the region is given
Locations of the public AEDs	DES	Locations of the public AEDs in the studied region
Location of the ambulance stations	DES	Location of the ambulance stations
Max/min reaction time	DES	Extremes of the uniform distribution from which the reaction times are extracted
Max/min CPR time	DES	Extremes of the uniform distribution from which the CPR times are extracted (only if mode=1)
Motivation threshold	DES/ABS	Minimum motivation a police officer requires to attend a voluntary training session.
Number of police officers	ABS	Number of police officers considered in the model
Probability for the network generation	ABS	Probability used to generate the network of contacts between agents
Network fatigue (ξ)	ABS	Network fatigue used in the motivation propagation algorithm
φ_i and φ_s	ABS	Motivation feedback superior and inferior extremes
Witness feedback interval	ABS	Interval for motivation feedback when the police was not first responder
Agents' attributes initialization parameters	ABS	All the parameters required to initialize the agents (section 3.2.2)

Table 3.4: All the input parameters of the model

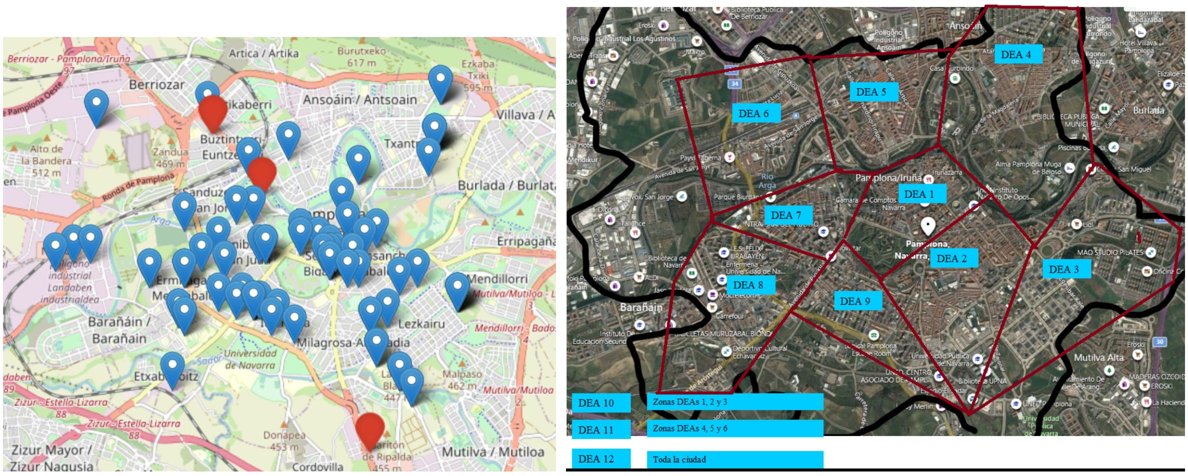
Chapter 4

Validation of the model, case studies and results analysis

In this section the hybrid model is going to be applied to a specific real scenario in order to validate some of its elements with real data. In addition, we sought to analyze in detail that scenario and make suggestions to improve the survival probability of OHCA patients in the studied region. First, the scenario is described together with the available data. Second, the model is applied to the area of interest following the AHA recommended CPR training frequency. The impact of the police intervention in the OHCAs is studied together with the efficiency of the training program. Finally, a different training program is proposed for the region that improves the overall police officer's training level.

4.1 Context and data

The studied region is the Spanish city of Pamplona. Pamplona is a small city located in the north of Spain, in the province of Navarre, it has 203418 inhabitants (2022). The bounding box that fits the city limits is defined by coordinates (-1.6953841057, -1.6046591827) longitude and (42.7888465848, 42.8427095180) latitude. The city has three ambulance stations, two of them are always available (this means that there are always available ambulances in that stations) and the third one is only available during the daytime hours. The two 24 hours available stations are located in the coordinates (-1.6650587175,42.8295239910) and (-1.6381896281, 42.7896666490); the other one is located in (-1.6566557989,42.8217334843). There are 94 public automatic external defibrillators, some of them are always available but others are only available on a specific schedule. The specific availability of each AED is known and can be obtained via the mobile application called *RÁPIDA* 8Gobierno de Navarra, 2019). Figure 4.1 a) shows the location of the 94 AEDs and the three ambulance stations. The local police of Pamplona has 443 officers, although not all of them patrol the city. Pamplona is divided into 12 patrolling regions, which are shown in Figure 4.1 b), these 12 patrolling sectors are all active during the daytime hours, during the night the patrolling regions are: number 10,11 and 12 and an additional region formed by the union of sectors 7,8 and 9. Police officers always patrol in pairs and, due the model assumptions, we suppose that at any given moment of time there is always one and only one police car in each patrolling region.



a) b)

Figure 4.1: a) Public AEDs (blue) in the city of Pamplona and Ambulance stations (red). b) Patrolling sectors of the local Police in Pamplona

The extrahospitalary emergency service of Navarre has provided us information about 628 OHCAs that took place in Navarre between 2015 and 2020. The quality of the registered information has some deficiencies, on one hand because some information is difficult to estimate (if there were no witnesses) such as the hour of the cardiac arrest, on the other hand because the first responders (police officers and EMS personnel) may not remember to register the required information when the OHCA occurs and after the OHCA they may have forgotten and therefore register imprecisely some important data. However, some information is automatically recorded and can be used to validate the model, for example the time the 112 was called, the activation time of the ambulance and the police car and the arrival time of the police officers or the ambulances. With that information the mean (and standard deviation) response time (in minutes) for the police and the EMS is computed: police 4.5 (3.6) 95% CI (3.16, 5.80) and EMS 9.5 (4.6) 95% CI (8.5, 10.51).

The model parameters that do not depend directly on the studied scenario or that are unknown, such as the police officers initial attributes values, are either going to be chosen following literature results, such as the learning rate beta distribution explained in Section 3.2.3, or using uniform distributions that reflect the unknown nature of that parameters.

4.2 Validation of the model using a real scenario

Scenario definition

Once the context and the available data has been explained, the model is applied to the city of Pamplona. Following the American Heart Association suggestions (American Heart Association, 2020) we consider a training program for the police agents consisting of one obligatory training session every two years. Now the model's parameters are going to be detailed following Table 3.4. Years of 360 days and months of 30 days are going to be considered. We are going to simulate 20 years. The bounding box is the city of Pamplona. Mode 0 is going to be used, this means that the basic CPR is always done by the pedestrian who witnesses the OHCA and the defibrillation and advanced CPR is given by the first responder to arrive: either ambulance, police or a pedestrian who has gone to find the nearest AED. The daytime hours are going to be from 8:00am to 22:00pm, with a probability of 0.75 of an OHCA occurring during the day. 52 cardiac arrest per year are considered, this is one each week on average. The obligatory training sessions take place every two years and there are not voluntary ones. We consider the speed of the pedestrians to be of 5km/h and the speed of the cars to be 70 km/h from 0:00am to 7:00am and from 23:00pm to 0:00am, 60 km/h from 9am to 13:30pm and from 15:30pm to 23pm, and 50km/h from 7am to 9am and from 13:30pm to 15:30pm, this is the time of the day with the highest traffic. In a meeting with the local police of Pamplona they suggested that the probability that the nearest police car is occupied is 0.3. The location of the public AEDs, the patrolling sectors and the ambulance stations are the ones stated in the previous section. According to Axelsson et al. (2012) the median time from arrest to start of CPR in a OHCA witnessed by a pedestrian is of 5 minutes, with that information we have assumed that the reaction time follows a uniform distribution in the interval $(4, 6)$. As we are only studying mode 0 we do not have to specify the distribution of the CPR time, because the CPR is done by the witness after the reaction time. We consider a motivation threshold to attend voluntary training sessions of 0.5. The total number of police officers in Pamplona is 443, however we consider only 140 in the model, the ones we assume that have patrolling duties, this assumption comes from the fact that there are 12 patrolling regions, each one is patrolled by one car with two officers, there are three possible working schedules and the number of officers considered should be duplicated to cover holidays and personal issues, this gives $12 \times 2 \times 3 \times 2 = 140$ police officers, which represents a third of the local police agents. We consider a contact network generation probability of 0.05, this is, we expect that each police officer is close friend with seven other agents. The network fatigue (ξ) is 0.2, this means that the motivation changes only propagate until four distance contacts of the affected agents. $\varphi_i = 0.9$ and $\varphi_s = 1.4$, the expected survival probability of the patients is 20% (obtained with some initial simulations of the model), with these parameter choices it is satisfied that $(1-0.9)*0.8 = (1.4-1)*0.2$, which means that the expected motivation of the agents is not going to increase to 1 or decrease to 0, but vary in the interval $(0, 1)$ during the simulation. To make this clear suppose that $\varphi_i = \varphi_s$, then because the death probability is 0.8 the agents will receive more often negative feedback than positive, which, if $\varphi_i = \varphi_s$, have the same magnitude, so the agents' motivations will tend to 0. When the two patrolling agents witness an OHCA attended by a pedestrian or an ambulance in which the patient survives, then both agents receive a feedback in the interval $(1, 1.1)$, as it has been explained in Section 3.2.5.

The agents' attributes are initialized as follows: the name is generated automatically *police_*+nº, the age is generated uniformly in the interval (2.25,4.5) because of the reasons explained in Section 3.2.2, the learning rate is generated following a beta distribution with parameters $\alpha_b = 1.8616257823384315$ and $\beta_b = 0.5045970105925269$, the motivation and the susceptibility are initialized uniformly at random in the interval $(0, 1)$, it is considered that all the police officers receive their first training session at the start of the simulation, this means that the initial NFA, γ and NFE is the learning rate and the initial UR is 0.

Design of experiments and results

The model is executed for 20 years and the following results are obtained. 1025 cardiac arrest occurred and 9 obligatory training sessions (the one at year 20 is not included). 95.609% of the cardiac arrests where attended by police officers, 3.51% by ambulances and 0.878% by pedestrians. Now the response times of each potential type of responder is going to be analysed, it is important to remember that the times considered are times from collapse to defibrillation, the time until CPR is the reaction time, because the CPR is done by the witness of the OHCA. The mean response time of the pedestrians has been of 22.167 minutes with a 95% confidence interval of (21.508, 22.826). Figure 4.2 shows an histogram of these times. It can be observed that the majority of times lay between 10 and 40 minutes, which is too much to assure the patient's survival, moreover, there are response times up to 65 minutes. The fact that the defibrillation times are too high means that the placement of the public AEDs is not providing a good coverage of the city. The mean response time of the ambulances (EMS) has been of 7.999 minutes with a 95% confidence interval of (7.9, 8.089), we can see that this result is a bit lower than the one estimated with the real data, it can be because the considered speed is a bit too high or because the real data considered a bigger area. Figure 4.3 shows an histogram of the ambulance response times, the distribution of these times is normal with the majority of times laying in the interval (6,10). The mean response time of the police officer has been of 5.586 minutes with a 95% confidence interval of (5.528, 5.644), this results agree with the real data. The histogram of these times is shown in Figure 4.4, the times range from 4 minutes, which is necessarily the minimum because the reaction time ranges between 4 and 6 minutes, and 9.5 minutes, this is, it is always below the required 10 minutes. The distribution of these times is not normally shaped, the majority of the times are between 4 and 7 minutes being times greater than 7 minutes an exception. The police agents' spatial distribution in the city is very different during the day and during the night, because the patrolling regions are reduced from 12 to 4, so it is expected the reaction times to be bigger during the night (mean 5.652, (5.531, 5.774)) than during the day (mean 5.564, (5.498, 5.63)). Figure 4.5 shows the distribution of the police response times during the day and during the night, it can be observed that during the night the response times are slightly higher, although it should be taken into account that during the night the police cars move faster.

Out of the 1029 OHCAs, 220 patients survived (21.46%). From those 220 patients 211 were attended by a police officer. Now the survival probability of the patients is going to be analyzed. For each OHCA we are going to compute the patient's survival probability as if it has been attended by each of the three responders separately, this way for each OHCA we have the survival probability of the patient if he/she had been attended by the pedestrian, the ambulance or the police. The mean patients' survival probability if the defibrillation was done by a pedestrian was of 0.0352 with a confidence interval of (0.0323, 0.0381). If the EMS always arrived first, the mean survival probability would have been of 0.143 with a confidence interval of (0.1400, 0.1458). If the police car arrived first then the mean survival probability would have been of 0.204 with a confidence interval of (0.201, 0.208). Notice, that the survival probability is higher when the first responder is the police, these is primarily due to the fact that they arrive faster in the majority of OHCAs. Figures 4.6 and 4.7 show the distribution of the difference in survival probability if the patient was attended by the police or by the pedestrian or ambulance respectively. Figure 4.6 shows that when the police officers arrive first

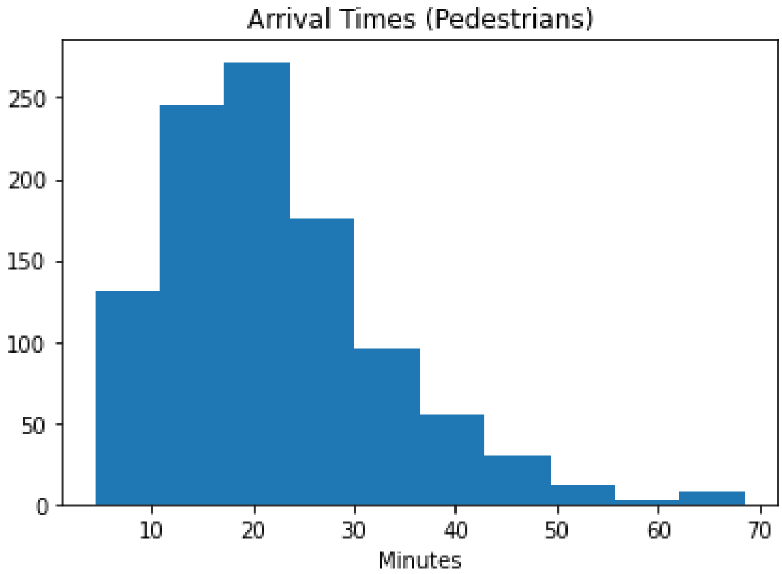


Figure 4.2: Histogram of the pedestrian response times

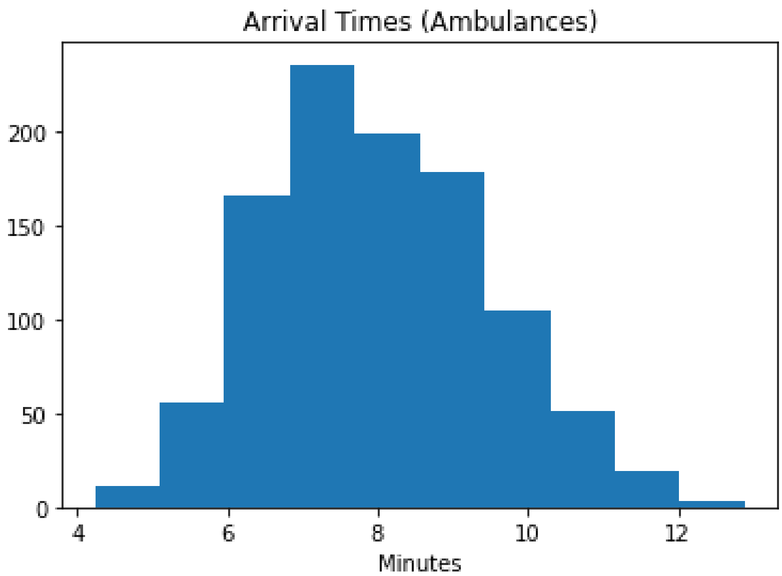


Figure 4.3: Histogram of the ambulance response times

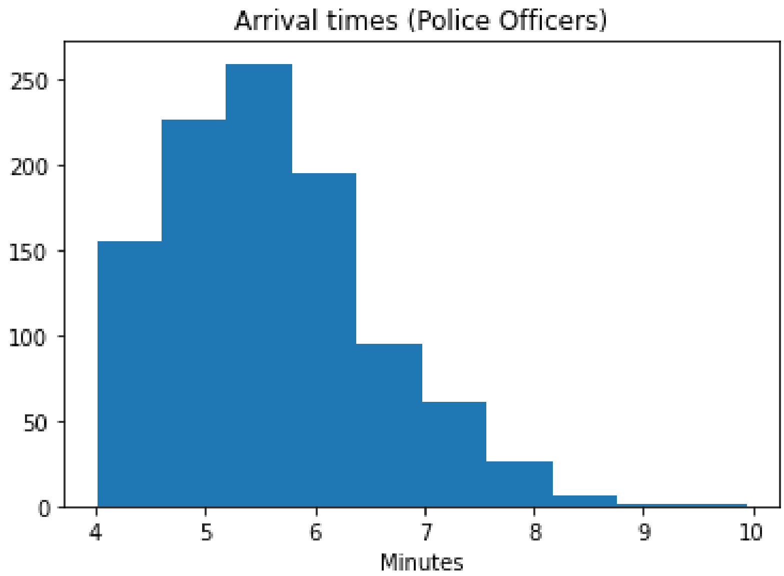


Figure 4.4: Histogram of the police agents response times

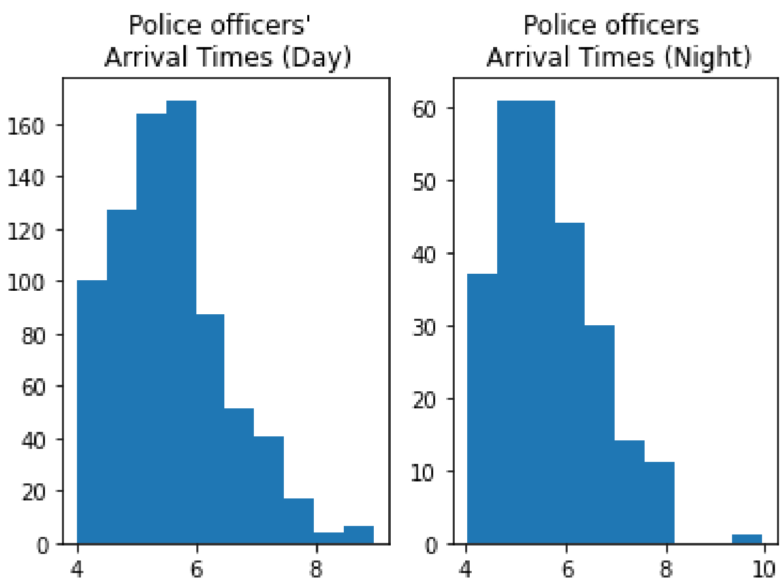


Figure 4.5: Histogram of the police agents response times during the day and during the night

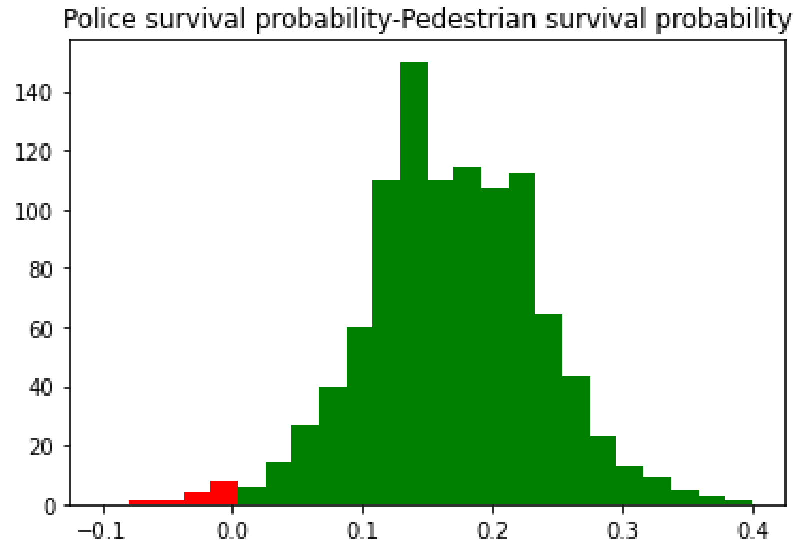


Figure 4.6: Distribution of the difference between the patient's survival probability if the patient was attended by the police or by a pedestrian.

there is a gain up to a 30% in the patients survival probability, the mean of the difference is 0.1692 (0.165, 0.173). With the ambulances (Figure 4.7) the histogram is shifted towards the left, however there is is still a significant gain in survival probability: the mean of the difference is 0.0614 (0.0588, 0.0637). Neither of the previous confidence intervals contained the 0, so the difference in survival probability is statistically significant in both cases. Figure 4.8 compares the difference between the police and the ambulances during the day (0.0625, (0.0599,0.06522)) and during the night (0.058, (0.052875, .06377)), it can be observed that during the night the gain is smaller.

Now we are going to study the evolution of the agent's attributes.

Figure 4.9 shows the daily evolution of the NFA of each of the 140 police agents in the model. The right figure shows a general image of the 140 agents' NFA, while the left figure highlights three of them. The initial values of the NFA are equal to the learning rates (α) of the agents, because we assumed that the agents attended their first training session at the start of the simulation, so they have learned $\alpha * 100$ percent of the total unknown knowledge, which at the start of the simulation is 1. This is why the initial NFAs follow a beta distribution. We can also conclude that, in this scenario, the absolute training level of the agents stays, in general, between 0.5 and 1. In the left figure NFAs modifications correspond to the obligatory training session every 2 years, although it may seem confusing that a training session decreases the NFA level of an agent, it should be remembered that the NFA is updated in every training session according to the current NFE level of the agent (Section 3.2.3). Thus, if the NFE is very low, the NFA may not increase to the same point as before, this is, the agent is not able to recover the same training level he/she achieved in the previous training session. Finally, notice that after the first training session (second year) the NFAs of the agents do not experience significant changes (they stay in a fixed interval), this is, the system appears to have reached an stationary state.

Figure 4.10 shows the daily evolution of the agents' effective training levels during the 20

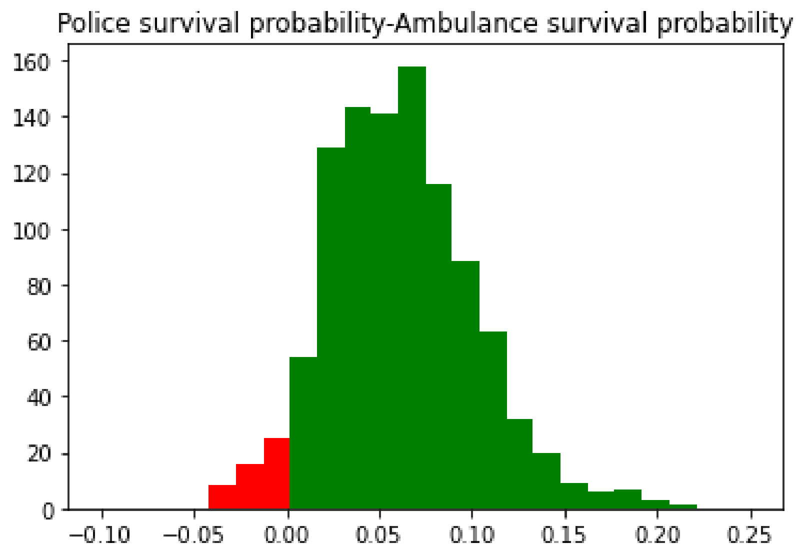


Figure 4.7: Distribution of the difference between the patient's survival probability if the patient was attended by the police or by an ambulance.

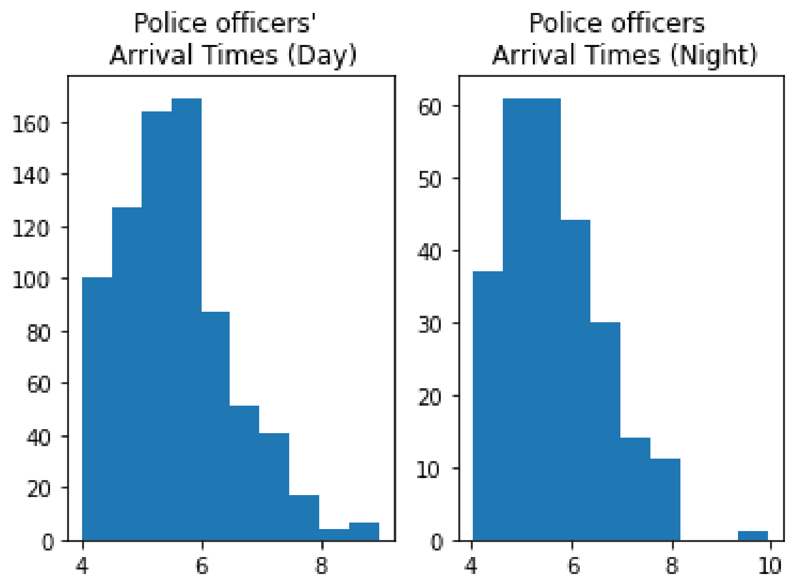


Figure 4.8: Distribution of the difference between the patient's survival probability if the patient was attended by the police or by an ambulance. Comparison during the day and during the night.

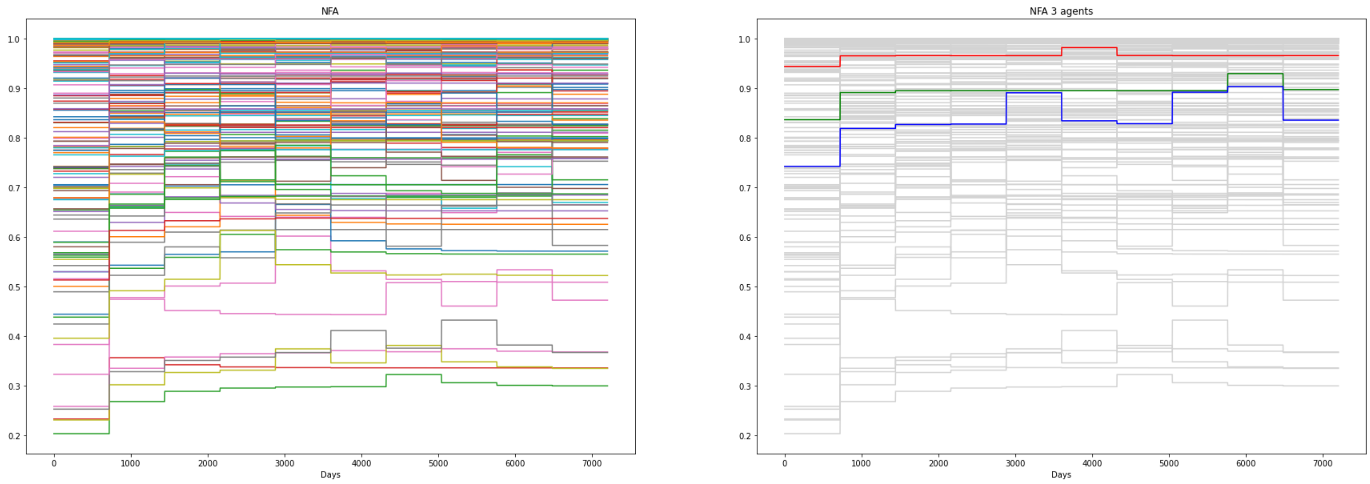


Figure 4.9: NFA evolution in the original scenario

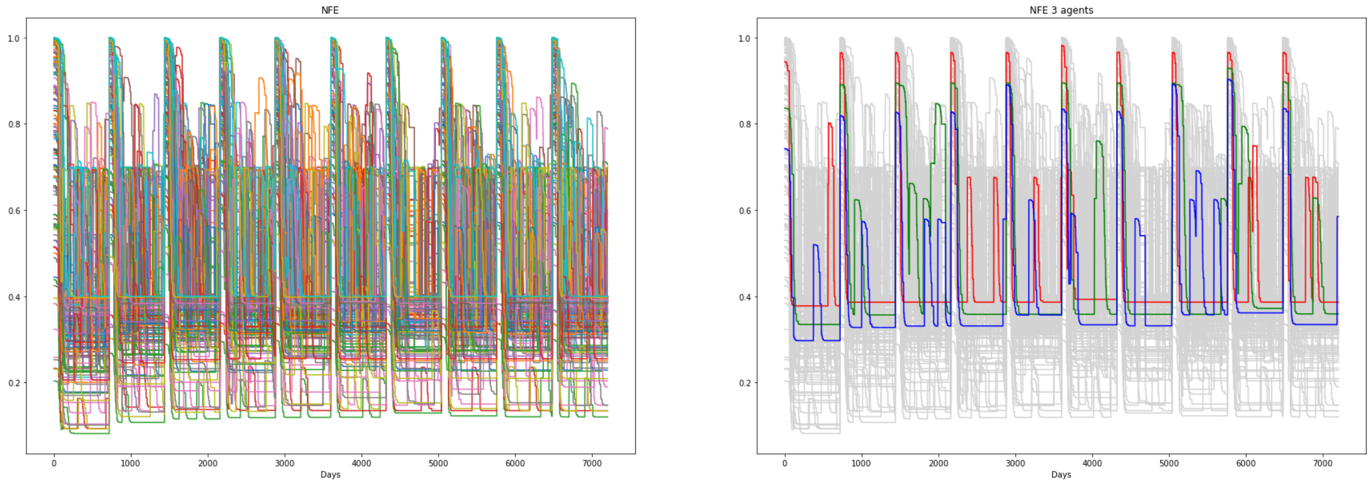


Figure 4.10: NFE evolution in the original scenario

years simulation time.Again, the left image includes all the police officers, while the right one highlights three of them (the same three as in Figure 4.9). The increases experienced by all the agents correspond to the biannual training sessions, they are a consequence of the NFA increase; individual increases correspond to the knowledge recovery as a result of attending an OHCA. Although it may seem that the NFE decreases are steep, it should be noticed that 20 years have been represented and the knowledge loss function is measured in months, after 6 months it reaches its limit. Just like the NFA, the NFE seems to stabilize after the first training session. Figure 4.11 shows the average NFE each day and the red line is a moving average with a 2 years window. From this figure we can conclude that the NFE stabilizes 4 years after the start of the simulation to a value near 0.43.

The evolution of the motivation is shown in Figure 4.12. We can see that the motivation is quite erratic and does not seem to stabilize. In addition, motivation changes occur much more often than NFA or NFE changes, but are slower in time. The magnitude of the changes depend on the agent's susceptibility, that is why some agents experiment greater changes than others.

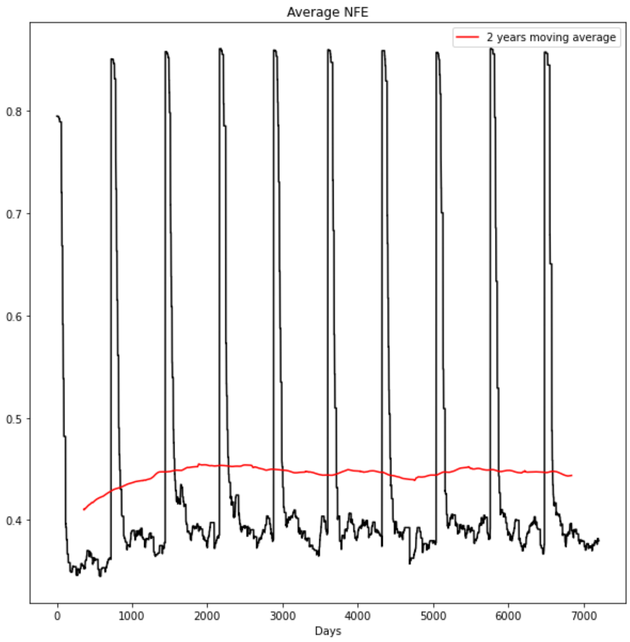
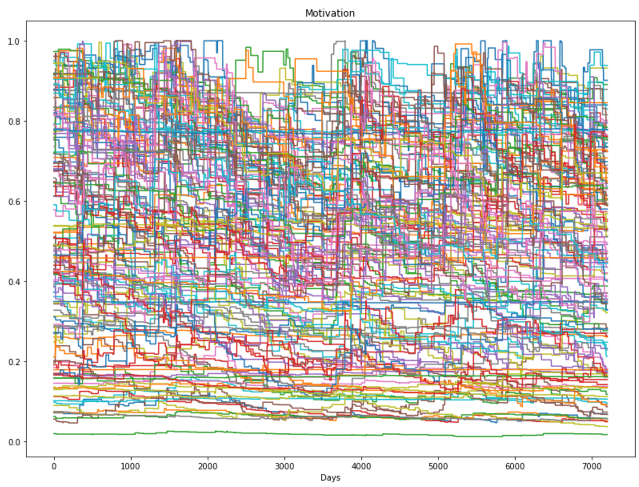


Figure 4.11: Average NFE evolution in the original scenario with 2 years moving average



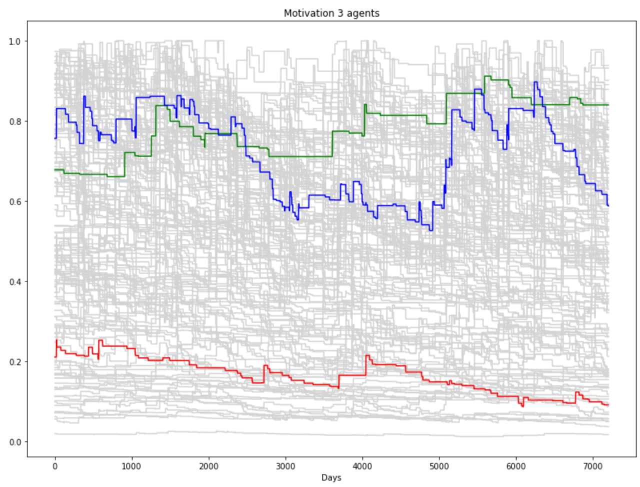


Figure 4.12: Motivation evolution in the original scenario

Conclusions

The results regarding response times and survival probability lead to the conclusion that equipping police officers with AEDs is a cost-effective measure. This is because when police officers arrive first at an OHCA incident, there is a significant improvement in the patient's survival probability. Additionally, the study highlights the observation that police officers often arrive on the scene before ambulances, further emphasizing the importance of their role in providing timely medical assistance.

From the evolution of the agent's attributes several conclusions can be extracted. First, the evolution of each police officer in the system is unique, and these individual behaviours affect differently the outcomes of the OHCA, thus, the use of a ABS model is justified. Second, after two to four years the system seems to stabilise and the average absolute training level of the agent's does not change significantly, while the average NFE follows a periodic time series, with 2 year period. Finally, regarding Figures 4.10 and 4.11 a great number of agents reach their minimum NFE level ($0.4NFA$) after each biannual training session, this is not desirable, because they do not accumulate knowledge from one training session to another, this is, they always go to the training sessions with the minimum possible knowledge and this does not allow them to experiment a significant improvement. However, the training sessions prove to be useful because there is an improvement in the moving average NFE during the first 4 years. Taking all of this into account we think it would be interesting to study a different scenario, in which a **new training program** is proposed consisting in biannual obligatory training sessions complemented with voluntary training sessions every 6 months. The next section analyzes in detail the new scenario.

4.3 Sensitivity analysis using an alternative scenario

In this subsection a variation of the AHA recommended training program is going to be studied. We are going to consider biannual obligatory training sessions (AHA recommendation) and voluntary training sessions every 6 months. The main objective is to avoid that the agents arrive at the training sessions having forgotten 60% of what they learned in the previous one, i.e. that they maintain their knowledge from one training session to the next. In this scenario we are going to focus in the evolution of the agents' attributes and in the average survival probability, but tests comparing police officers with pedestrians and ambulances will not be performed again. This scenario is going to be executed with the same parameters as the original one and with the same random seed, this is, the simulated OHCAs and responders locations and response times are going to be the same.

The evolution of the NFA is represented in the Figure 4.13. It can be observed that the majority of the NFA values stay in the interval (0.65,1), in addition, compared to the original scenario (Figure 4.9) the NFA changes more frequently and archives higher values, due to the voluntary training sessions. To check that the NFAs reach higher values we need to compare the blue NFA in the right image of both figures, the minimum value stays the same but it peaks higher with the voluntary sessions. After the sixth year, approximately, the NFA seems to stabilize.

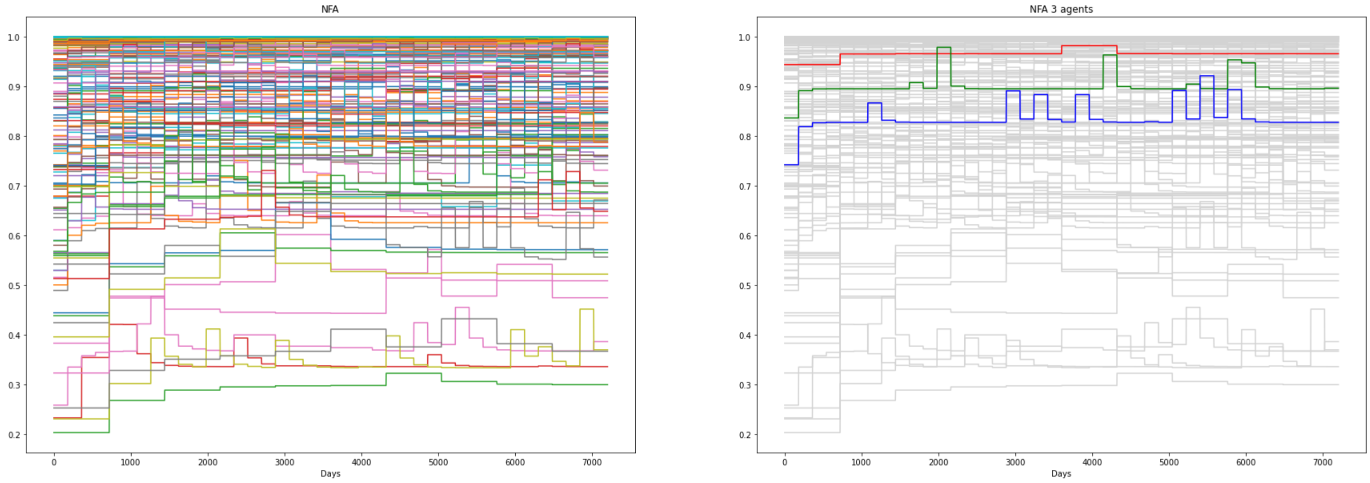


Figure 4.13: NFA evolution in the alternative scenario

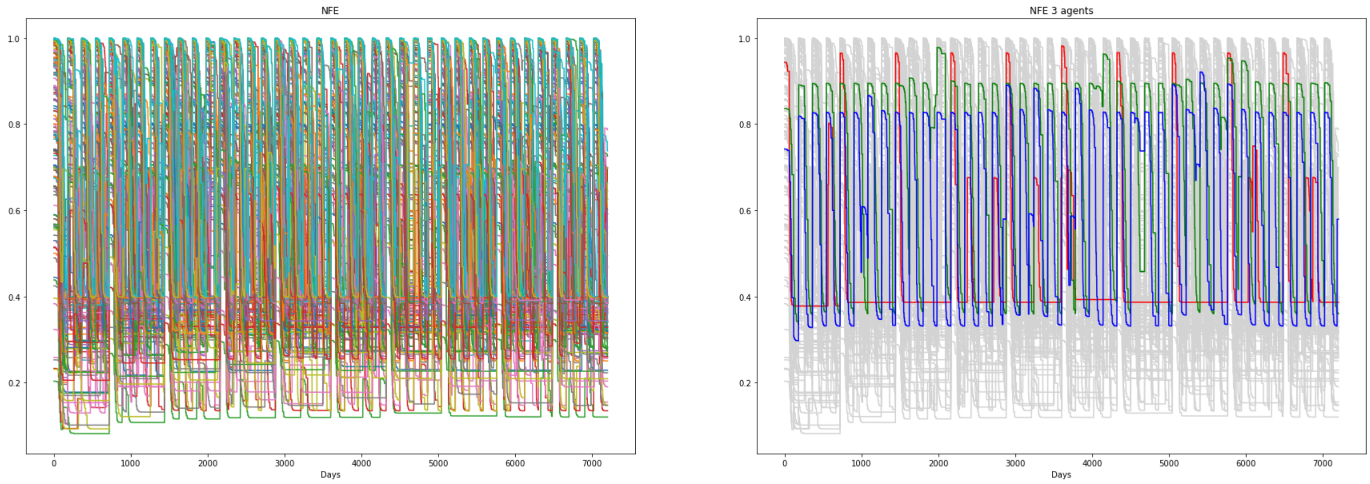


Figure 4.14: NFE evolution in the alternative scenario

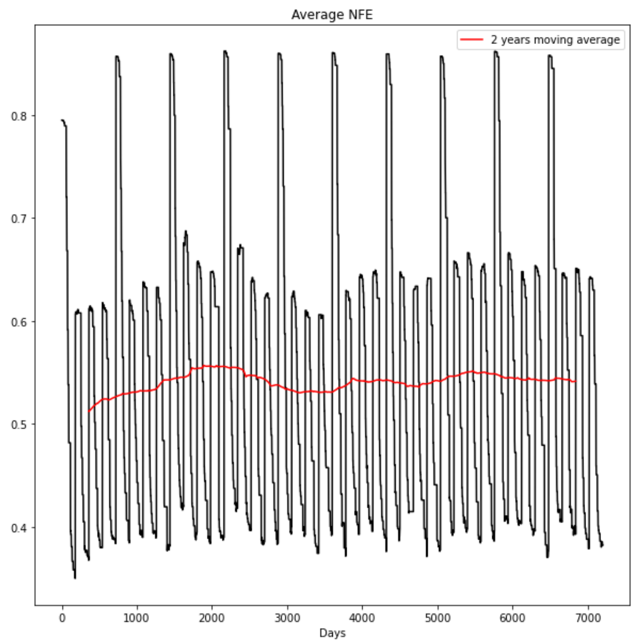


Figure 4.15: Average NFE evolution in the alternative scenario with 2 years moving average

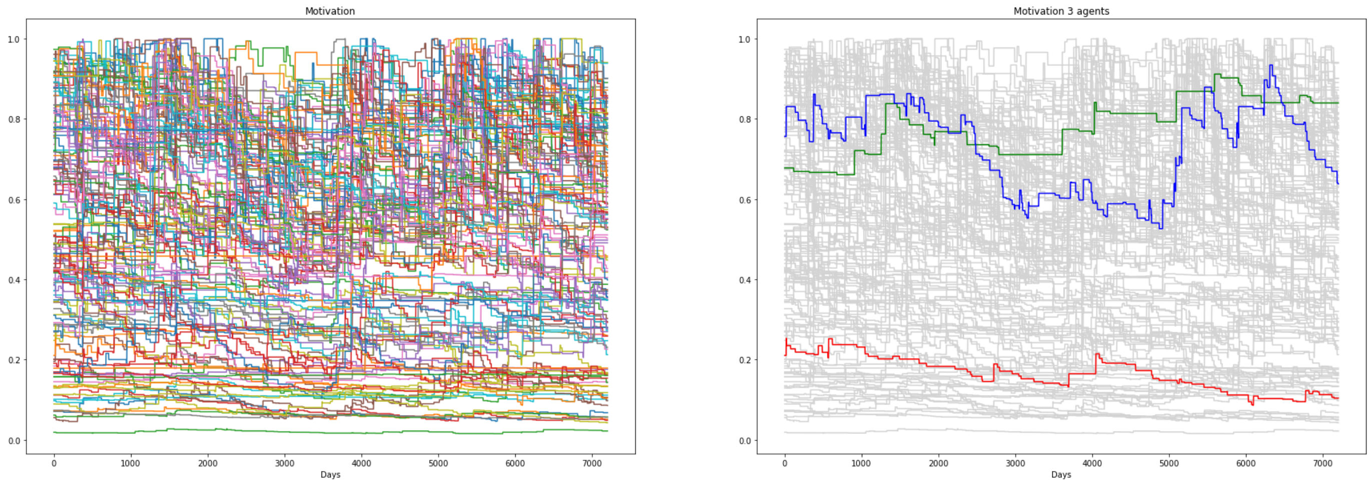


Figure 4.16: Motivation evolution in the alternative scenario

Figure 4.14 shows the evolution of the NFE in this alternative scenario and Figure 4.16 the evolution of the motivation. Both figures are related, because agents only attend voluntary training sessions if their motivation is higher than 0.5. From the evolution of the NFE we can say that there are many more peaks than in the original scenario, these peaks coincide with the voluntary training sessions. From the individual study (left image) we can see that even though the red police officer has the highest NFA, he/she has lower NFE than the other two agents (green and blue) most of the time, this is because the red officer is demotivated and does not attend voluntary sessions. This example highlights the importance of motivating the police officers and of having training sessions more often. The evolution of the motivation continues to be erratic and with small changes. Finally, Figure 4.15 shows the evolution of the daily average NFE with a moving average of 2 years, two aspects might be highlighted: the moving average is higher than in the first scenario, this is the police officers have a higher training level and the stationary state is reached in year 6, approximately.

To finalize this section, three graphics are going to be discussed in which both training programs and compared. Figure 4.17 compares the average NFE in both cases, it can be seen that with the modified training program the average NFE stays always higher or equal to the NFE with the original program. Figure 4.18 shows a comparison of the average annual survival probability in both scenarios, it is clear that there is a significant gain in patients' survival probability with the modified program. The mean difference in survival probability between the alternative scenario and the original one is 0.0145 with a 95% confidence interval of (0.013, 0.016). Finally, in Figure 4.19 the survival probability in both scenarios is computed taking the 25%, 50% and 75% percentiles of the CPR and defibrillation times and taking the average NFE of each scenario as training level. It can be observed, that the main factor that influences the survival probability is the time until CPR and defibrillation, nevertheless, the training level is also influential and can vary the survival probability up to 0.07.

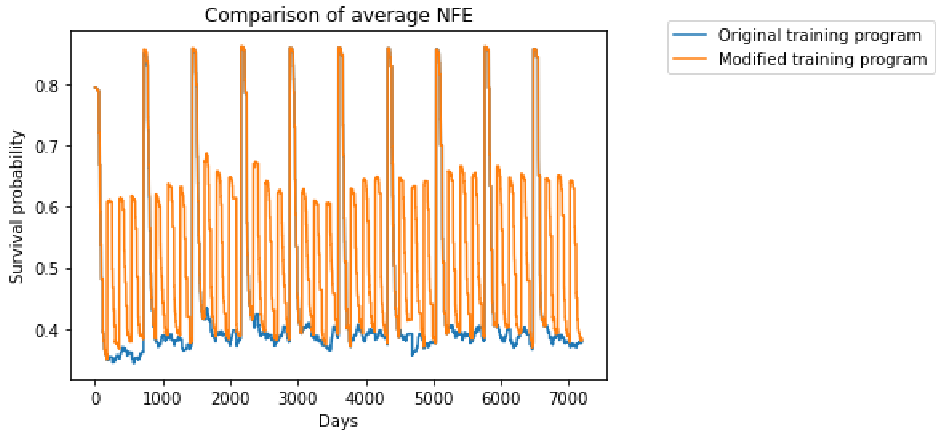


Figure 4.17: Comparison of the NFE evolution in both scenarios

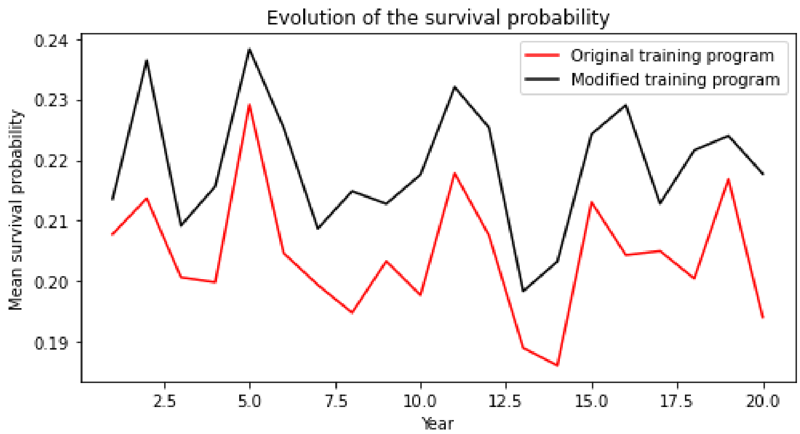


Figure 4.18: Comparison of the annual average survival probability in both scenarios

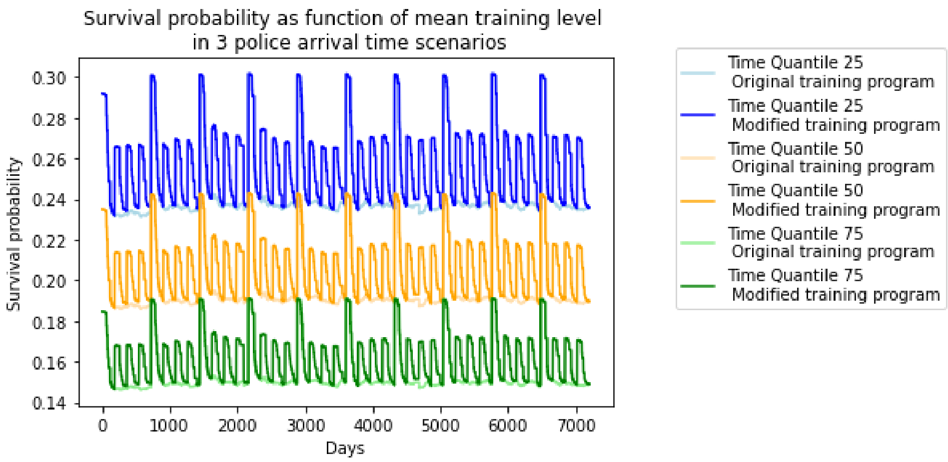


Figure 4.19: Comparison of the survival probability in both scenarios considering the average NFE in each scenario and 25,50 and 75 response times percentiles.

Chapter 5

Conclusions and future work

5.1 Conclusions

In this project an innovative and original model combining DES and ABS has been successfully developed to study the influence of local police in OHCA cases. The use of an ABS model has been fundamental to model the training level of the agents, which, at the same time, has been an influential factor in the survival probability of the patients. This project has contributed to the existing literature with two main aspects: the complete modelling of a local police agent in the context of extra-hospital emergencies and the modelling of the knowledge acquisition and loss processes, in infrequently used skills. The study of these processes in the context of CPR skills has been done in medical journals through surveys and examinations, however, the authors of this project are not aware of any other explicit mathematical modeling of these processes in the way that has been done in this project. Another innovative aspect of this project is the definition of a OHCA survival probability function, which explicitly includes the training level of the first responder.

The case study has reinforced the findings of many previous studies (Mosesso et al., 1998; Waalewijn et. al., 1998; and Myerburg et al., 2002) that police often arrive at the OHCA first, rather than the ambulances. In particular in the study conducted in the city of Pamplona, police cars arrive first in 90% of the OHCA cases, this is probably due to a non optimal distribution of the ambulance stations and to the fact that the number of police patrolling sector is much bigger than the number of ambulance stations. In the cases when the police arrives first there is a significant gain in the survival probability of the OHCAs' patients, this is why it is clearly recommended to equip and train local police in the use of AEDs. In the case studied, the gain in mean survival probability when the patient was attended by the police instead of by a pedestrian was of 17% and compared to the ambulance of 6%.

The case study has also brought to light that the AHA (American Heart Association) recommendation of retraining the potential first responders every 2 years is not enough, this result is in line with other previous studies (Cho and Kim, 2021; Adekola et. al., 2013; Broomfield, 1996; Moser and Coleman, 1992; Weaver et. al., 1979; Everett-Thomas et al., 2016), since agents forget what they have learned in the time between sessions. Providing the agents with a voluntary training every 6 months achieves a significant improvement in their training level and therefore in the survival probability. Time until CPR and defibrillation are the most influential factors in the survival probability, as it was expected, but the training level can also change the survival probability significantly, up to 0.07 in the studied scenario.

Finally, this project could not have been done without the help and the data provided by the local police of Pamplona and the external emergency service of Navarre. This emphasizes the importance of being in contact with real agents to achieve credible models and results with the potential of making a real impact on society.

5.2 Future work

In this project we have developed for the first time a hybrid model that extends the classical DES models by introducing the modelling of local police as agents that have their own learning and forgetting attributes that affect and are affected by the formative sessions and the participation in OHCAs. However, as a mathematical model it is a simplification and some aspects can be further developed. In this last section of the project some possible lines of future work are exposed.

First, it can be considered that when two agents attend together an OHCA, which always happens because they patrol in pairs, then the agent with the lower training level learns from the other agent. This will provide the model another source of agent-agent interaction and the individual evolution of the agents will be richer and closer to reality. However, how much does an agent learn from other agents when performing an OHCA is an aspect that has to be carefully thought. Another aspect that could be included in the model is the fact that if the police car and the ambulance arrive close in time to the OHCA then the ambulance is the one who attends the OHCA because they are the trained medical personnel. This consideration could potentially alter situations where the police have been considered the first responders, resulting in ambulances assuming that role instead. In addition, some times more than one police patrol may arrive to the OHCA, this may change the motivation propagation and learning of the agents. Another important aspect, that could be considered are the police officers working schedules and holidays.

From a design of experiments point of view, a bigger variety of scenarios can be studied, it has not been done in this project due to the fact that the main objective was the development, validation and testing of the new hybrid simulation model. However it is planned to use it, in cooperation with the local police and the emergency medical services of Navarre, to analyze different scenarios that could help the improvement of the attention to the OHCAs in the region. For this purpose, some ideas already discussed are: executing the model in mode 1, this is, assuming that the pedestrian that witnesses the OHCA does not start the CPR; considering a different configuration of patrolling sectors; and considering other distributions for the agents' initial parameters.

The model could also be used, not only to analyze the current situation, but also to optimize some aspects of the real system, such as the patrolling sectors of the local police. Trying to define the optimal patrolling sectors, that assure a wanted survival probability of the population with the minimum amount of police agents. The location of the public AEDs could also be optimized to guarantee an optimal coverage of 100 meters around each AED. Finally, the location of the ambulance stations is also susceptible of being optimized.

Finally the model could also consider rural regions, however in that cases additional considerations are needed, for instance which villages have police offices, where do the ambulances come from or whether or not the police officers are able to attend the training sessions without leaving their workplace unattended.

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