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Hospital Flood Emergency Management Planning using Markov Models and Discrete-Event Simulation

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Abstract

Disasters such as major floods affect all part of the globe. Hospital and healthcare structures are critical resources during such event and do not always benefit of emergency preparedness. When hospitals are impacted by the disaster, it puts a strain on the system and a reorganisation of all available hospitals on a given territory is necessary. As part of case study applied to the impact of floods on the Île-De-France region's health system, we present in this paper a simulation model that evaluates healthcare emergency plan by combining the healthcare process with the flood dynamics. The results can be used to elaborate an optimized strategy for evacuation and transfer operations. We provide a case study including several medical specialties and quantify the impact of several flood scenarios on the healthcare system.

Highlights

- Flood dynamics Markov model
- Patient flow discrete-event model
- Operational flood emergency management planning tool at the territory scale
- Evacuation decision tool for hospital manager

Keywords: flood; healthcare; emergency management planning; modeling; simulation

1 Introduction

1.1 Context

Like the majority of disasters, natural or man-made, floods can result in significant economic loss and human casualties. Disaster Operations Management (DOM) is a set of actions and decisions aimed at preparing responses to natural or man-made disasters by reallocating resources (e.g.

health facilities, transportation). The Federal Emergency Management Agency defines DOM as a cycle of four components: mitigation, preparedness, response and recovery [6] (Figure 1).

Mitigation activities take place before and after emergencies and aim at reducing the occurrence and the impact of a disaster. *Preparedness* activities take place before the disaster occurs to prepare the right response. A *response* is the application of the preparedness plans during the disaster by allocating the necessary resources to protect the community. *Recovery* includes actions taken to return to a normal situation after a disaster.

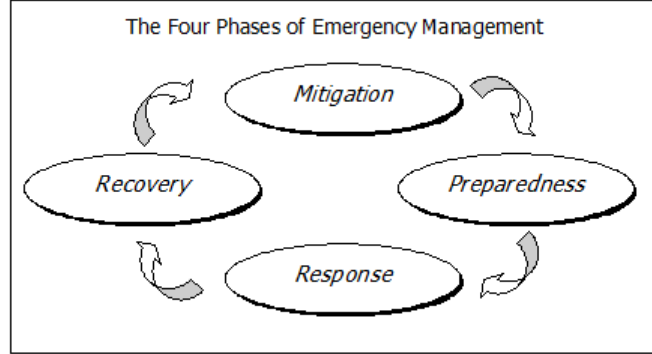


Figure 1: Life cycle of Disaster Operation Management.

Operations Research (OR) techniques can be used in several components of the DOM cycle. Lian and Yen [10] compares several risk calculation methods applied to flood mitigation. Wei et al. [16] use artificial neural network to predict flood occurrence and prepare for the impact. Artificial neural network is also used in [12] as well as geographical information system to predict the dynamic of water during the flood and to optimize the gate-control strategies. A classified survey of the use of OR techniques for DOM is presented in [2] and updated in [7].

One of the main challenges in DOM is the lack of resources [8], and understanding and managing critical resources is essential for the minimization of the disaster impact. Health facilities represent a key resource and must accommodate the usual patients flow and the flow resulting from a disaster [1]. However, hospitals may be themselves at risk of flood and therefore there is a simultaneous (i) increase of the demand for emergency services and (ii) decrease of their provision. In addition, when a hospital is flooded, its evacuation is more constrained than mass evacuation due to the patients' health conditions and the necessity to relocate them in appropriate facilities.

This research is supported by the Île-de-France Regional Health Agency (*Agence Régionale de Santé d'Île-de-France, ARSIF*). The mission of ARSIF is to implement health policy in the region. In particular, ARSIF is working on the anticipation, preparation and management of health crises. A practical study case that is the resilience of the healthcare facilities network of Île-de-France region (Paris, France) in case of a major flood is studied in this paper.

1.2 Objective and contributions

The main objective of this study consists in proposing a management tool for hospital evacuation planning in the event of a major flood of nearby rivers. Unlike most of the articles in literature, we integrate in our model (i) the flood dynamics (movement in space and time) instead of considering the impact at a predefined time using a Markov model, and (ii) the macroscopic patient flow model on a long horizon (one year) using a discrete-event model.

Hospital evacuation decisions adapt to the evolution of the flood and the model is used for both preparedness before the event and response during the event. We consider hospital

capacities on a macroscopic level: our model does not include detailed evacuation decisions from each building as proposed in several papers [3], but it allows to control the flow of patients over the different facilities. The resulting tool is used by the ARSIF for both strategic and operational control of evacuation in the event of a major flood.

This paper is organised as follows: after a short literature review (Section 2), we define the problem settings and present the general approach used in this work in Section 3. Next we present the flood model using Markov chain in Section 4. Section 5 defines the healthcare process model in a normal situation and during the event of flood. Several policies and strategies are implemented and applied to the process. Degradation of the process are measured using several key performance indicators, and the results for a case study are presented Section 6. Conclusions and perspectives are given in Section 7.

2 Related literature

In the literature, hospital evacuation operations have been approached in different ways: project management, mathematical modelling, simulation models and hybrid models [13]. In DOM, simulation models aim to evaluate several outcomes such as costs, mortality or focus directly on the building architecture (e.g. exits and staircases) that are used during evacuation [9].

In [15], a simulation model is developed to compare the impact of different resources on the evacuation operations. Results indicate that an increase of transportation resources (number of ambulances or transit rate) has a smaller benefit for evacuation than a change in the available capacity of the safe hospitals. In this study, disaster type is not specified.

The study [18] focuses on the analysis of the available capacity in safe hospitals in Florida, and estimates the absorption ability of the region in case of an earthquake. In [14], simulation is used to evaluate the effectiveness of an evacuation plan for one hospital under various scenarios and resources (e.g. patient types, nurses, number of ambulances).

A simulation model is developed in [3] to evaluate and improve the evacuation of one hospital in case of a flood considering internal resources (e.g. stretchers) and external resources (e.g. ambulances). In a previous work [19], a discrete-event simulation model was proposed to evaluate the impact of a flow on a network of hospital for strategic decision aid (decisions related to resource preparation and localisation to ensure feasibility of evacuations).

A systematic review of hospital emergency evacuation in disasters is presented in [17]. To the best of our knowledge, only one study [12] considers dynamic responses to the progression of the disaster (open or close gates). Other works focus on actions to be taken when the disaster is over. Studies dedicated to healthcare systems are often focused to a single facility.

The scientific objective of this paper is to fill a gap in the literature by providing a formal method that involves dynamic decisions during the progression of the disaster for a healthcare network using a modelling and simulation approach, taking into account a continuous flow of data related to the flood and hospitals characteristics.

3 Problem settings

3.1 Position of the problem

In this paper we intend (i) to mimic the behavior of the healthcare network using data from medico-administrative databases, and (ii) to evaluate the emergency plan of a regional healthcare system and assess the region’s resilience in case of flood, on the strategic level (several months before the supposed flood period) or on the operational level (a few days before the supposed start of the flood, taking into account meteorological information).

We define the region’s **resilience** as the ability to treat all scheduled patients and emergency arrivals within the region (i.e. with no transfer to hospitals outside of the region). In other words, the resilience is achieved if the non-flooded hospitals can take into care their patients as well as emergency patients and the patients coming from the flooded hospitals. In the context of very limited capacity, such solution may only be achieved by predefined management rules. For example:

- Discharging patients in order to free up as many resources as possible, before and during the flood.
- Preventive evacuation of high risk hospitals based on geographic location and electric fragility.
- Transfer of flooded hospital patients according to pre-established preferences.

Unlike most other disasters (natural and man-made), these rules are feasible in case of flood because of the alert period given by the weather forecast and water level measurements. However, the effectiveness of the flood management rules is highly variable depending on the flood dynamic (water level and speed) as well as the emergency patients flow.

3.2 General approach

To evaluate accurately the preparedness plan and the decisions before and during flood, the proposed approach presented in Figure 2 combines a patient flow model using Petri nets with a dynamic flood model using Markov chains. Data sources are depicted as green boxes, models as blue boxes, and dashboards as brown boxes.

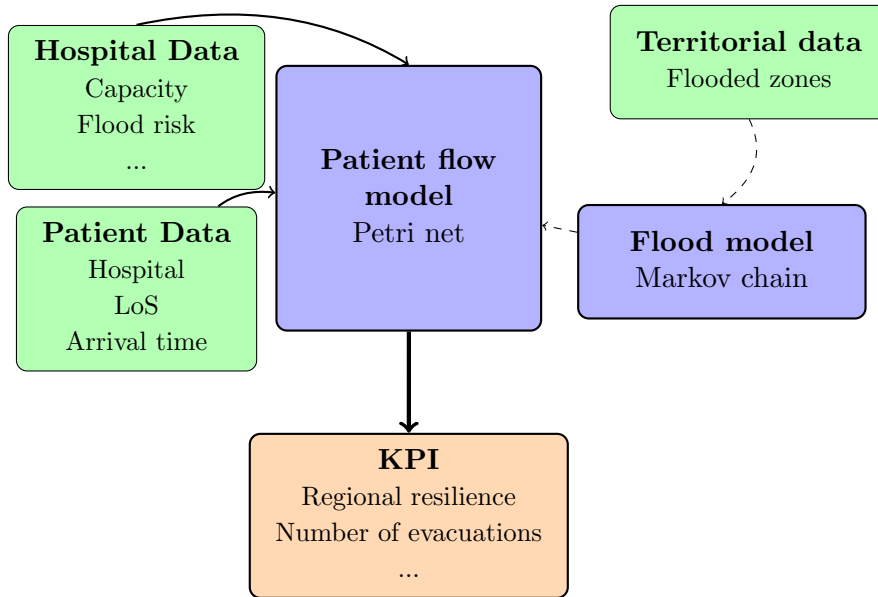


Figure 2: General approach

The patient flow model based on Petri nets is implemented in order to simulate all care pathways in all hospitals at the macroscopic level over a long horizon (at least one year) across the considered territory. The patient flow model replicates the operations of the healthcare network and is fed using real data coming from medico-administrative databases (Hospital Data

and Patient Data). Using this model, we apply a disturbance at a certain time (start of a flood) to evaluate the impact on the patient flow.

The flood model is a dynamic short term event (few days to few weeks). When the flood alert starts, healthcare processes are adjusted by including the flood management rules until the end of the flooding event. Such processes are considered as degraded care pathway (evacuation of the hospital and/or patients transfers).

The input data feed for the aforementioned models are: (i) hospital data (capacity per medical speciality and hospital, flood risk evaluation per hospital), (ii) patient data (referred hospital, length of stay, arrival time), (iii) geographical data (maps of counties within the region, flooded zones decomposition, transportation time).

Finally, several Key Performance Indicators (KPI) are computed to evaluate the performance of the management rules applied during the flood event. The main KPI is the evaluation of the autonomy of the region in case of major flood. The exhaustive list of KPI is presented in Section 6. In the following we formally define the flood model in Section 4 and the patient flow model in Section 5.

4 Formal flood modeling using Markov chain

A key contribution of this paper is to propose a flood model taking into account dynamics of water. We present in this section the set of assumptions we considered regarding the flood dynamic related to its starting time and its duration. Then a new Markov chain modeling flood dynamics is proposed. A comprehensive example describing how to build the model from real data is given in Section 6.

4.1 Assumptions on flood characteristics

The region is partitioned into zones. All the locations in a zone are impacted at the same level during each period of the flood. A flood is characterized by a sequence of water level values for each zone during rising and receding water times. Of course the water level values satisfy physical constraints related to geography of the ground and the stream-bed configuration. The speed and the extent of the flood is then characterized through the changes and maximal values in the matrix that defines a water level for each pair of zone and time period.

Obviously the water level is not constant during a time period. The value used can either be obtained by aggregating values over time (average, maximum) or taking a value at a specific time-stamp (beginning, middle or end of the period).

In order to link this geographical model with the healthcare network, we combine the zones coordinates with the geographic location of the facilities. We obtain the list of potentially flooded facilities for each water level. Accuracy strongly depends on the number (i.e. the size) of zones and the number (i.e. the length) of time periods involved in the model.

Assumption 1 (Starting time of a flood) *The starting time of the flood event is selected randomly to capture the impact of seasonality on the healthcare process as arrival distribution of patients varies depending on the period of the year.*

Assumption 2 (Flood types) *We consider two phases in a flooding event: (i) flood rising and (ii) flood receding. The length of the first phase determines if the flood is slow or fast. The total duration of the flood and the duration of both phases are selected randomly within realistic ranges extracted from historical data and validated by experts. This is a limitation of our experiments design since several phases of increase and decrease may occur during a flood.*

When a flood alert is triggered, the severity of the event remains unknown. We consider that the alert period allows the increase of preparedness to the worst possibilities. Consequently, all hospitals in the territory set a priority for their patients and free, if possible, a predefined percentage of their capacity. The performance of the rules applied during the alert period is reflected through the three following outcomes:

1. Less transferred patients in case of flood.
2. Better preparedness to face to the flow of emergency patients caused by the flood.
3. Excess capacity for patients transferred from flooded hospitals.

4.2 Markov model

Based on the geographical decomposition into zones and the time decomposition into time periods, we define a Markov chain with discrete index set (time) and discrete state space.

4.2.1 States definition

Let Z be the set of potential flooded zones indexed by z , and S_z be the set of possible states for the zones. For each zone we define a finite set of $n + 1$ states $\{0, 1, \dots, n\}$ with state 0 corresponding to a non-flooded zone and states $1 \dots n$ corresponding to water levels. The state values do not necessarily correspond to proportional water levels. These values are selected in order to model different impact level on the zone.

Water levels correspond to a flow value at each measuring station. Flow quantities can be easily sum up following the main river and its contributing rivers. Water levels are preferred, since they are more frequently measured and directly related to the flood severity.

A time horizon H discretized in time periods $\{1, \dots, t, \dots, H\}$ is considered to model flood dynamics. At each time period, the flood advances in the direction of the water flow (for example, the zones on the right (East) of Figure 7 are impacted first), and the changes of states follow that flow.

Consequently, we consider a Markov chain where each State $SR_i = \{s_1, \dots, s_{|Z|}\}$ of $|Z|$ items representing the water levels of all the region zones at a time period. The time period index is discarded from the state definition since it is only used to decide on the phase, flood rising or receding.

An example of flood simulation using our Markov chain is proposed in Figure 3 in five zones. No flood is occurring during periods 1 and 2. Zones 1 and 2 are flooded at level 1 during period 3, and then at level 2 during period 4 whereas zones 3 and 4 are flooded at level 1, etc.

t_1	(0, 0, 0, 0, 0)	No flood
	↓	
t_2	(0, 0, 0, 0, 0)	No flood
	↓	
t_3	(1, 1, 0, 0, 0)	Zones 1 and 2 are flooded level 1
	↓	
t_4	(2, 2, 1, 1, 0)	Zones 1, 2 flooded at level 2, zones 3, 4 flooded at level 1

Figure 3: Example of flood dynamics

4.2.2 Initial State

A flood may start at one or several different zones depending on the number of rivers. We suppose that the flood event always starts at State SR_0 :

$$SR_0[z] \geq 1 \text{ if } z \text{ is a source zone of a river, } 0 \text{ otherwise.} \quad (1)$$

In the example of Figure 3, the flood starts at t_3 from zones 1 and 2.

4.2.3 Transition Rules

The probability to reach state SR_j from state SR_i is denoted p_{ij} . A transition rule defines how the level of water is changing between two consecutive time periods. Three types of transitions or transition rules are applied in our model : loop, increase and decrease:

- **Loop transition.** The same state SR_i with a probability p_{ii} is kept for all zones between two time slots. The loop transition periods allow to control the speed of the flood rising and receding.
- **Increase and decrease transitions.** The first (flood rising) and second (flood receding) phases are symmetrically controlled by the following rules.

In order to keep the flow of water consistent with the flood direction, the water level in any downstream zone z is lower (resp. upper) than the level in the upstream neighboring zone z' during the previous period. Equations (2-3) and (4-5) enforce these constraints for State SR_j that follows SR_i for the increase and decrease transitions, respectively.

$$\forall z \in Z, SR_j[z] \leq SR_i[z] \leq SR_j[z] + INC_{max} \quad (2)$$

$$\forall z, z' \in Z, SR_j[z] \leq SR_i[z'] \quad (3)$$

$$\forall z \in Z, SR_j[z] - DEC_{max} \leq SR_i[z] \leq SR_j[z] \quad (4)$$

$$\forall z, z' \in Z, SR_j[z] \geq SR_i[z'] \quad (5)$$

Note that the rules are applied to the normalized water levels of the states definition.

Between two consecutive states a maximal increase INC_{max} (resp. decrease DEC_{max}) values are defined. Combined with the length of the time periods, these values limit the water rising and receding speed.

We assume that the flood is rising (resp. receding) in all the zones at the same time. As in the example of Section 6.3, slow floods in Paris area satisfy this statement. However some extensions may consider zones in different phases at the same time. But, consistency with the physical constraints of the water flow should be revised.

The rules (2) to (5) enforce consistency between neighbor zones according to the current episode, rising or receding, by limiting the set of reachable states from State SR_i . Of course, the transition probabilities p_{ij} have two values; one for each episode.

When few historical data are available, like in our study case described in Section 6, the first value to set is the stationary state probability p_{ii} , since this is the most common case for slow floods. Then the probabilities of reachable states $SR_j, j \neq i$ are set to the same value $p_{ij} = (1 - p_{ii}) / Card(\{j \neq i : SR_j \text{ is a reachable state}\})$.

4.3 Monte-Carlo simulation

The proposed Markov chain model is integrated in a DES (Discrete Event Simulation) model in the following way: at each time slot, an event of the DES model is triggered in order to activate the transition probabilities of the Markov models. Depending on the result, the states of the zones are updated, resulting in the triggering of new management rules in the patient flow model described in the next section.

5 Patient flow model

In this paper the patient flow model is defined on a macroscopic scale and specific to a medical specialty. The complete healthcare network is composed of multiple instances of patient flow models, one for each medical specialty.

5.1 Assumptions on patient flow

Data are related to hospitals and patients, as detailed below. In our case study, facilities are all hospitals (but other types of facilities can be considered in our model). The capacities of hospitals have a major role in our model as the available capacity of a non-flooded facility can absorb the flow of patients caused by the flood (emergency and evacuation). Moreover, patients have specific needs depending on their health troubles. For instance, a dialysis patient needs a bed specifically equipped for dialysis. Therefore the capacity of each facility is defined by a multidimensional vector with one value for each specialty.

We consider 3 health states for each patient:

- State 1 (ps_1): the patient must be taken care of on the scheduled date, or if they are already hospitalized, their care must continue,
- State 2 (ps_2): the hospitalization may be delayed by a week maximum,
- State 3 (ps_3): the hospitalization may be delayed by a week or more.

Hospitals and patients data sets are used as input of the discrete-event model. Basically, patients arrive to facilities with specified arrival rate to receive care in a specialty for a given length of stay. The patient's specialty does not change during their stay. Parameters used in the model are summarized in Table 1.

Table 1: List of parameters

Parameter	Definition
$S = \{1, \dots, s, \dots, S \}$	Set of medical specialties
$H = \{1, \dots, h, \dots, H \}$	Set of hospitals in the network
$n_{s,h}$	Number of beds of specialty s in hospital h
$Flex_s$	Binary indicator that equals 1 if delaying patients of specialty s in states ps_2 and ps_3 during a major flood allows the continuity of care of all patients in the state ps_1 , 0 otherwise.

Assumption 3 (Binary impact on the flood on hospitals) *We suppose that if a hospital is flooded, it must be evacuated (all the patients are transferred).*

Assumption 4 (Independence of specialties) *Specialties are considered separately since we assume no transfer between medical specialties is permitted during the flood. The autonomy of the region in the event of a flood can therefore be evaluated for each specialty separately.*

5.2 Healthcare management strategies during a flood

When a hospital is flooded, hospitalized patients must be transferred. Also, future scheduled patients and emergency patients are referred to other hospitals during the entire flood period. During the flood period, disaster management operations (especially transportation) are complex and involve several decision makers. We define two strategies for patients' transfers based on organization and feasibility constraints.

1. Strategy 1: patient transfer is prioritized depending on transportation resource management. Thus, depending on the available capacity in the relevant specialty, a patient will be transferred as first choice to a hospital in the same hospital group, then in the same department (county), then outside the county but within the same region, and finally outside of the region (Figure 4).
2. Strategy 2: we define an isolated territory which does not include any major critical bridges. Depending on the available capacity in the relevant specialty, a patient will be transferred to a hospital in the same isolated territory. The purpose is to prevent helicopter transportation outside of the territory which is costly and should be avoided as much as possible. If all hospitals in the territory are saturated, patients will be transferred outside of the region (Figure 5).

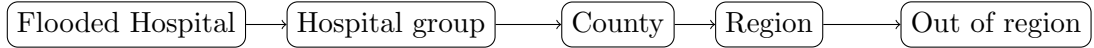


Figure 4: Strategy 1 for evacuations and transfers.

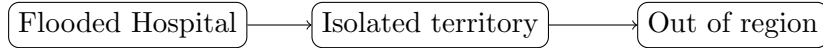


Figure 5: Strategy 2 for evacuations and transfers.

Regardless of the selected strategy, all impacted hospitals remain closed after the end of the flood event for repair purpose. The duration of the repair depends on the cause of the impact (submersion or electrical failure).

5.3 Petri Net Model of Patient Flow

5.3.1 Basic notions of Petri nets

An ordinary Petri net (PN) is a 4-tuple $\mathcal{R} = (P, T, F, M_0)$ where P and T are two disjoint sets of nodes called respectively places and transitions, $F \subseteq (P \times T) \cup (T \times P)$ is a set of directed arcs, $M_0 : P \rightarrow \mathbb{N}$ is the initial marking of the net.

The set of input (resp. output) transitions of a place $p \in P$ is denoted by $\bullet p$ (resp. $p\bullet$). Similarly the set of input (resp. output) places of a transition $t \in T$ is denoted by $\bullet t$ (resp. $t\bullet$).

A transition $t \in T$ is said to be enabled at M_0 if for all $p \in \bullet t$, $M_0(p) \geq 1$. A transition may fire if it is enabled. The firing of a transition t at marking M removes one token from each of its input places and puts one token to each of its output places.

A source transition is a transition without any input place. A source transition is always enabled. A sink transition is a transition without any output place. When firing a sink transition, all tokens are removed respecting usual rules but no tokens are generated.

A T-timed Petri net is a 5-tuple $\mathcal{R} = (P, T, F, \theta, M_0)$ where $\theta : T \rightarrow \mathbb{N}$ assigns to each transition t its transition firing time $\theta(t)$. Firing a timed transition t at time d removes immediately

one token from each input place but add tokens to its output places only at time $d + \theta(t)$. In this paper, we use a T-timed Petri net because we need to take into account duration of hospital stays.

A colored Petri net is a 7-tuple $\mathcal{CPN} = (P, T, C, A, W^+, W^-, M_0)$ where $C : (P \cup T) \rightarrow \Omega$, $C(p)$, $p \in P$, is the set of colors associated to a place p (i.e. the set of colors that place p may have), $C(t)$, $t \in T$, is the set of colors associated to a transition t (i.e. the set of ways to fire t), $W_{p,t}^- : C(t) \rightarrow \mathbb{N}^{|C(P)|}$ is the pre-condition of a transition in relation to a color which defines for each way of firing t the required combination of tokens of different colors in different places, $W_{t,p}^+ : C(t) \rightarrow \mathbb{N}^{|C(P)|}$ is the post-condition of a transition in relation to a color which defines for each way of firing t the combination of tokens of different colors added to different places. In this paper we use a colored Petri net in order to take into account the various medical specialties during the hospital stays.

5.3.2 Model description

In order to formally define the patient flow model, a colored T-timed Petri net model for each specialty $s \in \{1, \dots, |S|\}$ is proposed in Figure 6. Patients arrivals are modelled using a source transition $t_{s,1}$. Place $p_{s,1}$ models the decision related to the triggering of a degraded mode for patient care in the event of a flood. If the facility is not impacted, transition $t_{s,2}$ is fired (transportation time within the same facility) and the patient stays in the facility by firing transition $t_{s,3}$. The transition duration is defined by a random variable that depends on the type of stay. When the patient exits the facility (patient discharge), sink transition $t_{s,4}$ is fired.

In the event of a flood, the degraded mode is triggered. Transitions $t_{s,5}, t_{s,6}, t_{s,7}$ model transfers to other hospitals following a predefined priority. Transition $t_{s,8}$ is a special case and models the transfer to an hospital out of the region, that penalizes the resilience of the region. In that case, we do not consider the stay of the patient and thus transition $t_{s,3}$ is skipped. For the Strategy 1, $t_{s,5}$ models a transfer to a facility from the hospital group, $t_{s,6}$ models a transfer to a facility from the county, and $t_{s,7}$ models a transfer to a facility from the region.

Place $p_{s,4}$ models the available beds for each hospital having the specialty s . Then we have as many ways of firing $t_{s,3}$ as we have hospitals having beds to take into care patients related to specialty s .

The resulting model is replicated for all medical specialties of the region. Formally the Petri Net of Patient Flow (PNPF) for a medical specialty s is a 7-tuple colored Petri net $\mathcal{PNPF}_s = (P_s, T_s, C_s, A_s, W^+, W^-, \theta_s, M_{s,0})$ where:

- $P_s = \{p_{s,1}, p_{s,2}, p_{s,3}, p_{s,4}\}$ is the set of places.
- $T_s = \{t_{s,1}, \dots, t_{s,8}\}$ is the set of transitions.
- $C_s : (P_s \cup T_s) \rightarrow \Omega$, $C(p)$, $p \in P_s$, is the set of colors associated to a place p (i.e. the set of colors that place p may have) and $C(t)$, $t \in T_s$, is the set of colors associated to a transition t (i.e. the set of ways to fire t). Here $C_s(p) = \{cp_0\} \forall p \in \{p_{s,1}, p_{s,2}, p_{s,3}\}$, $C_s(p_{s,4}) = \{cp_1, \dots, cp_{|H|}\}$, $C_s(t) = \{ct_0\} \forall t \in T - \{t_{s,3}\}$ and $C_s(t_{s,3}) = \{ct_1, \dots, ct_{|H|}\}$. Thus cp_0 is the color of patient tokens and $cp_1, \dots, cp_{|H|}$ are the colors of tokens modelling beds in hospitals, one color for each hospital.
- A_s is the set of arcs of the PN.
- $W_{p,t}^- : C(t) \rightarrow \mathbb{N}^{|C(P)|}$ is the pre-condition of a transition in relation to a color which defines for each way of firing t the required combination of tokens of different colors in different places. Here all transitions have only one color except $t_{s,3}$: $W_{p_{s,2}, t_{s,3}}^-(ct_0) = 1$ (we need a patient token to start the stay) and $W_{p_{s,4}, t_{s,3}}^-(ct_h) = (0, \dots, 1, \dots, 0)$ where 1 is at rank h , $\forall h \in H$ (we need a bed in a hospital of the network).

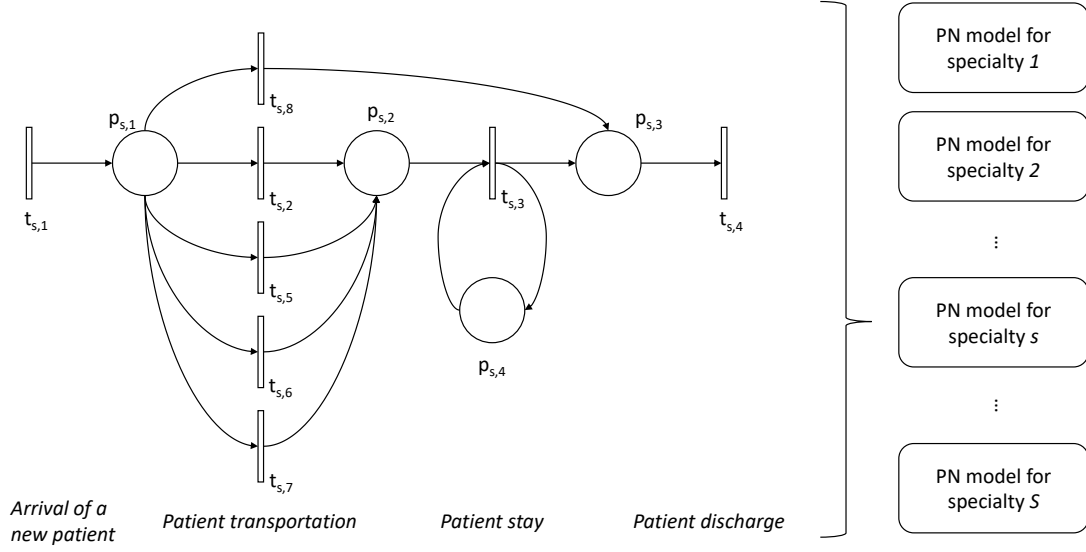


Figure 6: Generic patient flow model

- $W_{t,p}^+ : C_s(t) \rightarrow \mathbb{N}^{|C_s(P_s)|}$ is the post-condition of a transition in relation to a color which defines for each way of firing t the combination of tokens of different colors added to different places. It is defined symmetrically as $W_{p,t}^-$.
- $\theta_s : T_s \rightarrow \mathbb{N}$ is a function returning the firing duration for a transition of the PN.
- $M_{s,0} \in \mathbb{N}^P \times \mathbb{N}^{|C_s(P_s)|}$ is the initial marking of the PN. Here place $p_{s,4}$ has as many tokens of color cp_h as hospital h has beds for medical specialty s .

5.4 Simulation of the Patient Flow Model

Anylogic Pro 7.1 has been chosen to implement both the patient flow model and the flood dynamic model. The implementation of the Petri net model in a simulation software is straightforward: source and sink transitions are implemented using source and sink modules. Decision places are implemented using decision nodes. Transportation or facility stay (temporized transitions) are implemented using process modules.

A virtual event is triggered periodically (following the time periods defined in the Markov chain) during the simulation in order to update the Markov chain states. Global variables describing the flow state are updated. Depending on these values, output of place $p_{s,1}$ is chosen accordingly to the currently used management rule and the flood state.

5.5 Key Performance Indicators

As introduced above, the ARSIF coordinates the evacuation operations and the patients transportation over the region during a disaster. Therefore we choose a set of KPIs that quantify the impact of each scenario and identify the decision makers involved (hospital groups, counties or the entire region).

Following the sequence of evacuation and transfers, Table 2 defines the list of indicators measured in this experiment.

Table 2: Key performance indicators.

E_{Tot}	Number of evacuees for the entire region
E_{HG}	Number of hospitalized patients evacuated to a hospital in the same group
E_{Dep}	Number of hospitalized patients evacuated to a hospital in the same county
E_{Reg}	Number of hospitalized patients evacuated to a hospital within the region
E_{IT}	Number of hospitalized patients evacuated to a hospital within the isolated territory
E_{Out}	Number of hospitalized patients evacuated to a hospital outside the region
T_{Tot}	Number of transferred activities for the entire region
T_{HG}	Number of transferred activities to a hospital in the same group
T_{dep}	Number of transferred activities to a hospital in the same county
T_{reg}	Number of transferred activities to a hospital within the region
T_{IT}	Number of transferred activities to a hospital within the isolated territory
T_{Out}	Number of transferred activities to a hospital outside the region
$Auto$	Binary indicator that equals 1 if the region remains autonomous, 0 otherwise

6 Case study: Paris region flooding

In this section, we present some results obtained on the Paris region healthcare network which has been impacted by a flood of the Seine and Marne rivers. We use several flood scenarios obtained by the Markov chain model and real data for different specialties. The usual period of major flooding is from November to April. Consequently, most preparedness plans are designed according to the pattern of patients flow during this period. However, flooding may occur at any time of the year, causing the sub-optimality of some of the emergency management rules (e.g. June 2016 flood in Paris).

6.1 Data and Scenarios

Several specialties were treated in the experiments and we choose to present as example the results for general medicine as well as a synthesis of other specialties.

The French national hospitalization database (*Programme de Médicalisation des Systèmes d'Information*, PMSI) is an exhaustive nationwide medico-administrative database that covers the data of patients in both public and private hospitals. We extract from this database the dates of start and end of stays of patients of all hospitals for every considered specialty.

Data collected from the hospitals in the Paris region are summarized in Table 3. Hospitals provided for each specialty their capacity, the number of patient per month, the mean length of stay. The flood risk is evaluated for each flood scenario by mapping the hospitals locations and the flood coverage.

Table 3: Hospitals and patients data for the studied specialties.

Specialty	Number of hospitals	Maximum flooded hospitals	Maximum electrical failures	Total capacity	Patients per year	Mean LoS (in days)
General medicine	189	12	53	20,601	1,748,569	3.9

In these experiments, we consider 24 scenarios based on the combination of the two following parameters:

- Flood starting time (month): The flow of patients of each specialty strongly depends on the month of the year. It is important to test the impact of a flood on several periods during the year.

- Transfer strategy: Represents the priority sequence selected for the evacuation of hospitalized patients and transferred activities, as presented in Figures 4 and 5.

We ran 1000 replications per scenario. Depending on the specialty, the computing time of one replication is between 5 and 15 seconds. All the results presented below are mean values of the replications.

The patient process Petri net model is calibrated using (i) hospitalisation medico-administrative data for length of stay modelling and (ii) geographical data for transportation duration. For each medical specialty, we fit a lognormal distribution for the length of stay in the hospital (transition t_{s_3} and an exponential distribution for the inter-arrival duration (transition $t_{s,1}$ in Figure 6). For each pair of hospitals of the considered region, a transportation duration is modelled using a triangular distribution (the minimum value is the required transportation duration without traffic, the maximum value corresponds to the duration with heavy traffic, and the mod value corresponds to the most observed transportation duration).

6.2 Flood characteristics

The flood model proposed in this paper is based on the detailed maps of regional zones. These characteristics can be used in order to evaluate transfer strategies face to potential scenarios.

6.2.1 Zones

Water level and flow are monitored by reference stations. We consider that for each reference station there is a potential flood zone (PFZ), *i.e.*, a zone in our Markov chain model. An example of reference stations and 15 associated zones is shown in Figure 7.

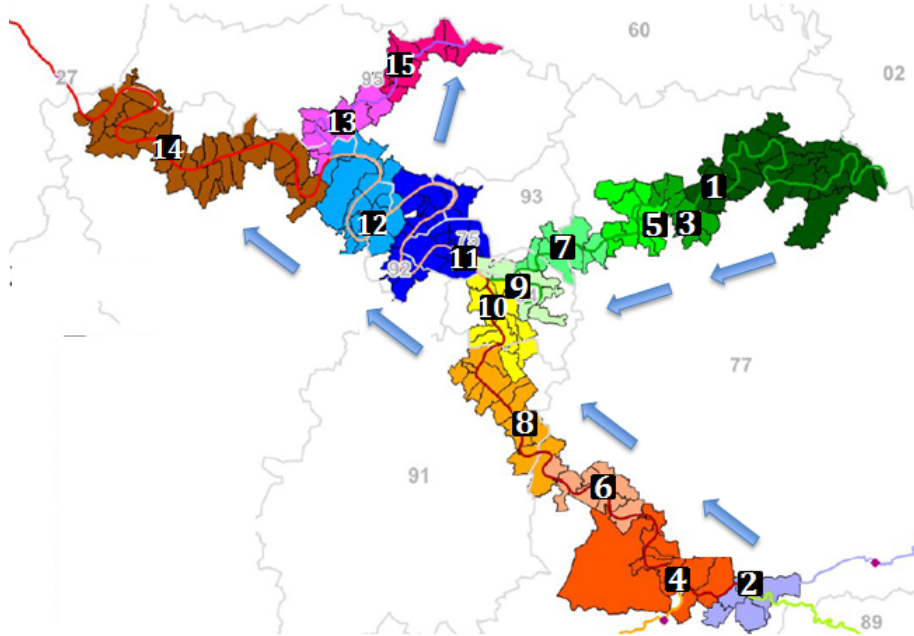


Figure 7: Water flow and the potential flooded zones associated to reference stations.

6.2.2 Water levels

The water levels that define possible states of each zone are computed relatively to a reference flood. Based on the results of a hydraulic model ALPHEE [5], the Regional and Interdepartmental Directorate for Environment and Energy designed regional scenarios to estimate the impact of floods in the Paris region.

These scenarios use a set of simplified maps of flooded zones according to the flow of the main rivers in the region and are proportional to the flood of 1910, one of the most devastating floods in the region. Figure 8 shows examples of the impact of the three most important scenarios representing, from left to right, 80%, 100% and 115% of 1910's flood. These scenarios are respectively denoted *R0.8*, *R1* and *R1.15* in the rest of the paper.

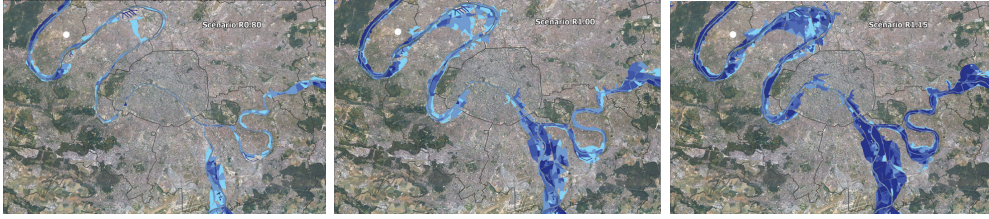


Figure 8: Three regional flood scenarios in Paris region as a percentage of 1910's flood.

We use these data to set four possible states to each zone, as shown in Table 4.

Table 4: Notation and definition of zone states relatively to 1910's flood.

State of the zone $z \in Z$	Definition
$s_z = 0$	The zone is not flooded
$s_z = 1$	The zone is impacted by the scenario <i>R0.8</i>
$s_z = 2$	The zone is impacted by the scenario <i>R1</i>
$s_z = 3$	The zone is impacted by the scenario <i>R1.15</i>

Figure 9 shows an example of the combination on a sub part of the map. The yellow areas represent the flooded area in case of scenario *R0.8*, the pink in case of *R1* and the blue areas in case of *R1.15*. The hospitals are represented by the orange dots.

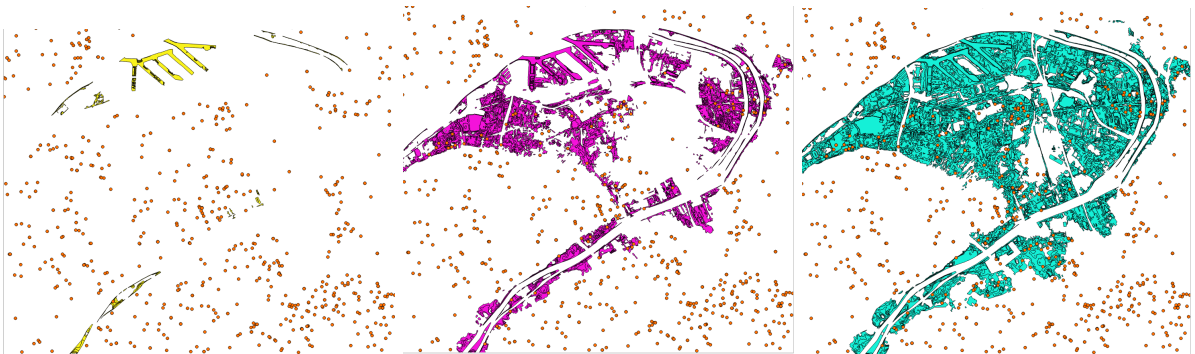


Figure 9: Example of the mapping of the three scenarios and hospitals locations

Compared to static maps, our model is able to easily deal with many possible scenarios that mix the water levels of reference scenarios *no-flood*, *R0.8*, *R1* and *R1.15* among zones.

In this case study, we tested the impact of a slow flood on the territory, as it is the most frequent one for the Paris region.

6.3 Flood Markov model validation

The parameters (water levels, time periods and transition probabilities) of the Markov chain model are set according to the flood in Paris (2016) in order to validate our approach.

In the current section, the flood model is run starting from different time periods, in order to measure the convergence of the model when real information is revealed time to time.

Reference water levels are real data collected from [4]. These data are simplified through a subset of five zones along the Seine river which correspond to the five measuring stations located after the main rivers confluences.

The eleven water levels considered in the Markov chain model are computed as one tenth of the gap between the maximum expected level (115% of the 1910 flood) and the default level.

Real water levels reached by the flood are given at the top of Figure 10 from 2016-05-28 to 2016-06-12. The corresponding normalized water levels according the 1910 flood are given in the bottom graph of Figure 10.

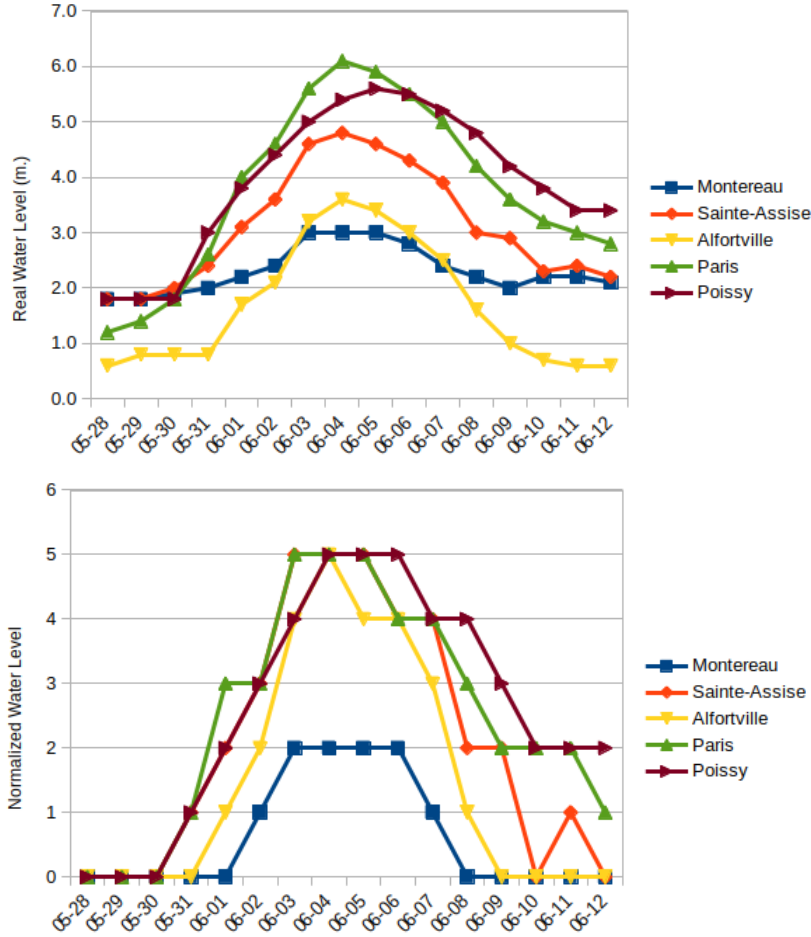


Figure 10: Water levels at five measuring stations during the 2016 flood in Paris

We defined empirically the values of the parameters of the flood of 2016. The stability probability $p_{ii} = 0.3$, the maximal increment for flood rising or receding is equal to 2. In Figure 11, the forecasts performed at three different days are displayed. The forecast computed on 2016-05-28 is displayed in the top graph, on 2016-06-02 in the middle graph, and on 2016-06-06 in the bottom graph. Actually, the forecast for next days can be refined when new measures are collected and used for a warm start of the Markov chain model. The values displayed are averaged over one hundred runs.

The average error over one hundred independent runs of the forecast at the first day (2016-05-28) of the simulation was 1.77. The error is computed as the average deviation between every real and forecast water level (with normalized units), at every station, every day and for every run.

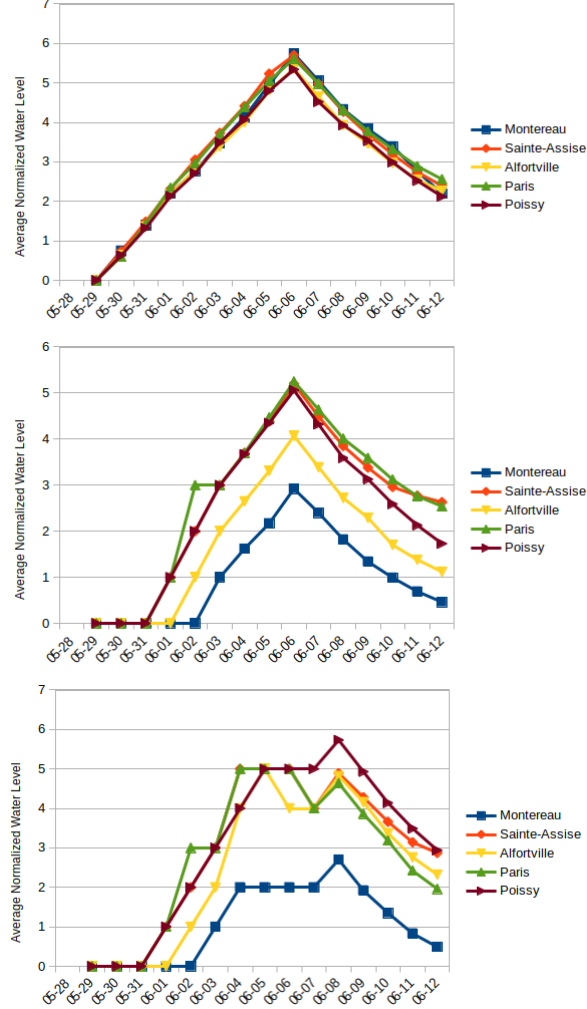


Figure 11: Update of forecasts on 05-28, 06-02 and 06-06

Flood simulation model is validated using historical water levels: for one possible flood dynamic we want to test, we adjust probabilities of the Markov model in order to match the real flood. This way it is possible to test the impact of slight variations of a flood on the hospital network.

6.4 Patient flow model validation

There are several ways to validate a simulation model. In [11], the author summarises and presents 15 of the most commonly used validation techniques. Among these techniques, we selected *historical data validation* for our problem: since we have historical data, part of the data is used to build the model and the remaining data are used to test whether the model behaves as the system does.

Patient flow model is constructed using 80% of historical data to build distributions used in the model. Then we inject the patients from the other 20% of historical data in our simulation

model (without any flood occurring) and we compare the KPI length of stay of patients against the actual values. We used a 90% confidence interval and we verified our average length of stay for each specialty is within the given confidence interval.

Figure 12 presents the validation results for all medical specialties taken into consideration in this case study. Note that the simulation model under estimates the length of stay for neuro-vascular and long term care patients. This phenomenon is caused by the occurrence of extreme points in the historical data for these specialties. After discussing with practitioners, we consider the results given by the model are fair considering these particular cases. Also, for dialysis, length of stay is always equal to one. Apart from these 3 particular cases, simulation results are validated as the historical data sample average always fit in the error interval of the simulation results.

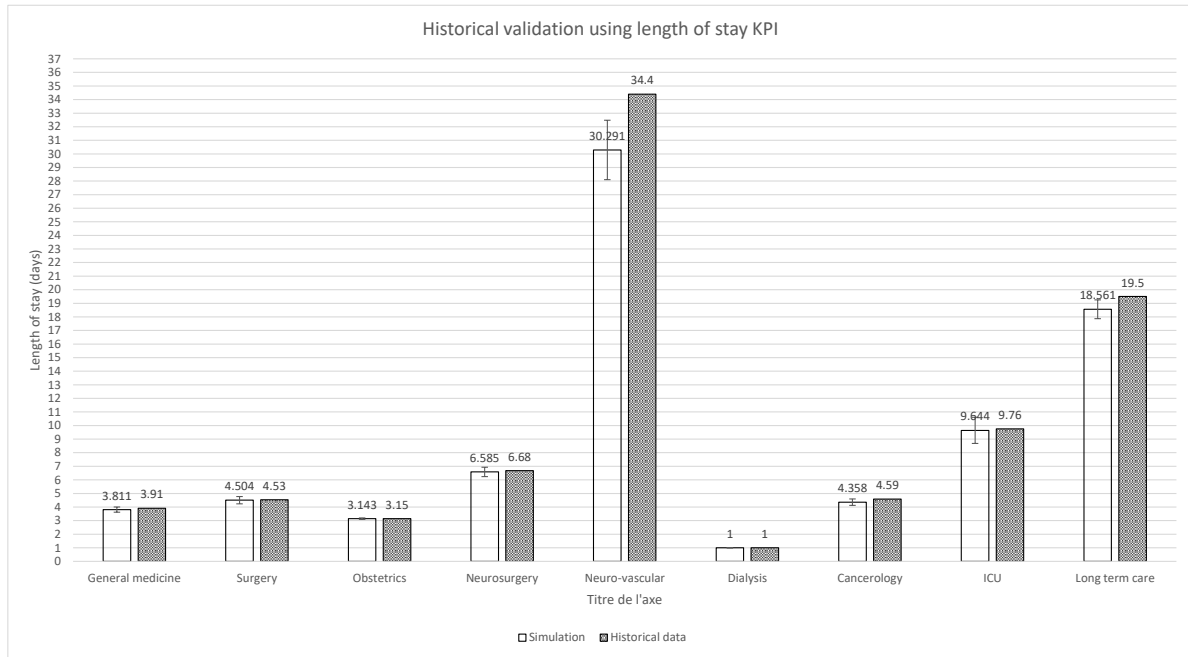


Figure 12: Validation results

6.5 Results

6.5.1 General medicine speciality

In the region, 65 institutions are likely to be affected by a flood, of which 12 are due to flooding and 53 to electrical failure. On average, a flood requires the evacuation of 1,500 hospitalised patients and nearly 10,000 scheduled or urgent activities are displaced during the flood and the repair period (Figure 13). There is an impact of seasonality on the activity of general medicine. The months of May and August are the least critical, while the months of June and November are the most critical.

Electric frailty is the main cause of flood impact on health facilities: 80.52% of the evacuated patients and transferred activities are due to an electrical power failure, whereas the remaining 19.48% of evacuation are caused by an actual flooding of the hospital. The next results represent the indicators of the absorption ability of the region depending on the scenarios.

Scenario 1 In Scenario 1, we suppose that the major bridges are functional and can be used for evacuation and transfer operations. Using this sequence of priority, the region remains

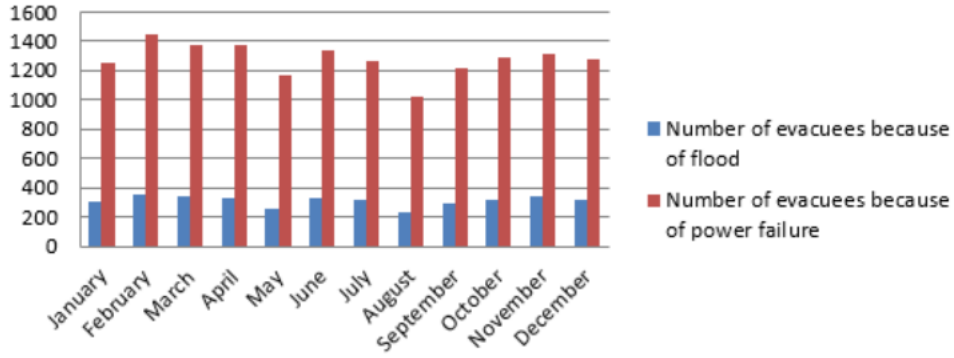


Figure 13: Number of evacuees and transferred activities in the region

autonomous for healthcare ($Auto = 1$). Moreover, the flood impact is absorbed within the county for evacuations and activity transfers. Table 5 shows that hospital groups absorb most of the evacuees from impacted hospitals. This result has a major advantage as hospital groups may share patients files as well as human and material resources. Transfer of activities are less absorbed by the hospital groups but still remain in the same county. We also observe that seasonality have little impact on the distribution of evacuees and transferred activities. In this scenario, no hospitalized patient (resp. no medical activity) is evacuated (resp. transferred) outside of the region.

Table 5: Percentage of hospitalized patients evacuated to a hospital in the same hospital group (E_HG) (resp. same county (E_Dep), same region (E_Reg), out of the region) and number of activities transferred in the same hospital group (T_HG) (resp. same county (T_Dep), same region (T_Reg), out of the region) for Scenario 1

Beginning of the flood	Patients evacuations				Transferred activities			
	E_HG	E_Dep	E_Reg	Out	T_HG	T_Dep	T_Reg	Out
January	78.83%	21.17%	0.00%	0.00%	5,187	4,899	0	0
February	77.65%	22.35%	0.00%	0.00%	5,318	5,278	0	0
March	78.14%	21.86%	0.00%	0.00%	5,621	5,722	0	0
April	78.39%	21.61%	0.00%	0.00%	5,209	5,236	0	0
May	78.71%	21.29%	0.00%	0.00%	4,191	4,248	0	0
June	78.36%	21.64%	0.00%	0.00%	5,677	5,649	0	0
July	80.11%	19.89%	0.00%	0.00%	4,419	3,746	0	0
August	81.85%	18.15%	0.00%	0.00%	4,428	2,808	0	0
September	78.95%	21.05%	0.00%	0.00%	5,538	5,247	0	0
October	78.15%	21.85%	0.00%	0.00%	5,638	5,431	0	0
November	77.72%	22.28%	0.00%	0.00%	5,743	5,696	0	0
December	78.47%	21.53%	0.00%	0.00%	5,176	5,155	0	0

Scenario 2 In Scenario 2 the main bridges are not functional and thus evacuation and transfers must stay within isolated territories. Isolated territories absorb 97% of evacuations and transferred activities as shown in Table 6. The remaining 3% of patients therefore need out-of-region transfers. In this strategy as well, seasonality have little impact on the number of evacuees and transferred activities.

Technically, this strategy is very difficult to implement in real life for a logistical reason. Transportation resources are managed by either hospital groups or counties. An isolated territory

Table 6: Percentage of hospitalized patients evacuated to a hospital in the same territory (E_IT) (resp. same county (E_Dep), same region (E_Reg), out of the region) and number of activities transferred in the same territory (T_IT) (resp. same hospital group (T_HG), same county (T_Dep), same region (T_Reg), out of the region) for Scenario 2

Beginning of the flood	Patients evacuations				Transferred activities				
	E_IT	E_Dep	E_Reg	Out	T_IT	T_HG	T_Dep	T_Reg	Out
January	97.93%	2.07%	0.00%	0.00%	10,657	54	198	0	0
February	97.66%	2.34%	0.00%	0.00%	11,013	69	222	0	0
March	97.69%	2.31%	0.00%	0.00%	11,187	57	195	0	0
April	97.74%	2.26%	0.00%	0.00%	10,325	28	148	0	0
May	97.78%	2.22%	0.00%	0.00%	8,097	15	102	0	0
June	97.90%	2.10%	0.00%	0.00%	11,771	39	174	0	0
July	97.75%	2.25%	0.00%	0.00%	10,073	11	130	0	0
August	97.81%	2.19%	0.00%	0.00%	6,996	15	100	0	0
September	97.80%	2.20%	0.00%	0.00%	10,919	25	149	0	0
October	97.96%	2.04%	0.00%	0.00%	11,316	25	147	0	0
November	97.86%	2.14%	0.00%	0.00%	10,889	39	181	0	0
December	97.70%	2.30%	0.00%	0.00%	10,212	40	191	0	0

may contain several counties, and a hospital group may have establishments in several isolated territories. An extra effort is needed to coordinate the cooperation between several decision makers.

In general medicine, an average of 13% of patients must be treated immediately (ps_1), 30% can be postponed for several days as needed (ps_2) and more than 56% can be rescheduled in one to several weeks (ps_3). By studying the lists of patients and their states, decision makers may avoid evacuations and transfers outside of the region.

6.5.2 Other specialties

As mentioned previously, several major and critical specialties were studied in our work. Each specialty necessitates detailed modeling of the healthcare process as well as specific management rules in case of a flood. We summarize in Table 7 the results obtained : the averages on all the replications of the number of evacuations and transfers, the probability of autonomy for the two selected strategies, the impact of seasonality and the flexibility of the specialty.

Table 7: Hospitals and patients data for the studied specialties.

Specialty	Flexibility	Nb of evacuees	Nb of transfers	Autonomy Strat1	Autonomy Strat2	Season. impact
Surgery	YES	1027	6715	100%	99%	YES
Obstetrics	NO	500	1661	100%	82%	NO
Neurosurgery	NO	122	200	100%	98%	YES
Neuro-vascular	NO	1	41	100%	78%	YES
Dialysis	NO	324	1338	100%	92%	NO
Cancerology	YES	86	422	100%	100%	YES
ICU	NO	490	1222	100%	98%	NO
Long term care	NO	2558	861	100%	86%	NO

For all the studied specialties, regional independence is guaranteed if the major bridges and roads are available (Strategy 1). On the other hand, the independence of the isolated territories

is not always guaranteed: in the worst case (neuro vascular unit), the probability of independence of the isolated territory amounts to 78%. This means that in 22% of flood scenarios, patients must be evacuated and activities transferred outside the region. For many specialties, there is no flexibility in the rescheduling due to the states of the patients. However, it is possible to free more capacity in other specialties and avoid the loss of the regional autonomy.

7 Conclusions and perspectives

We presented in this paper the work realized with the Regional Health Agency that aims to evaluate healthcare emergency plan and assess the regional resilience in case of major flood. We developed a modeling and simulation approach that combines a healthcare process model with a flood model using Markov chain. The model is used both as a preparedness tool and a response tool for healthcare decision makers. The results obtained on real data allow us to validate the model and estimate the impact of several flood scenarios on each specialty. The measured key performance indicators also identify the decisions makers involved for each scenario (the hospital groups, counties or isolated territories).

In future work, additional evacuation strategies will be tested depending on more than the hospitals capacity and political preferences. Moreover, optimization models should be integrated to the model to solve several disaster operations problems, such as transportation operations and human resources assignment.

A Appendix: Software Development

A visualization interface is integrated to the model using the AnyLogic software and the Java programming¹. It is intended to be used by medical authorities in order to visualize the flood impact and organize the response accordingly. Several parameters are selected at the start of the simulation:

- The initial date of the simulation - a drop-down menu to choose the start day and month;
- The initial force of the flood - a choice between the intensities of 80, 90, 100, 105 and 115 representing the water levels;
- The force and speed variations of the flood - a choice between “no variation”, “low variation” and “high variation”.
- The availability of major bridges and roads - this choice defines the evacuation strategy.

To visualize the evolution of the simulation we used the Map tool provided by AnyLogic. The flood evolution is illustrated by colored zones corresponding to the water level (on the map of Figure 14).

When a hospital is damaged, its color changes depending on the cause of damage (active, flooded or power failure). KPI measures are visible through data graphs and updated with the flood evolution.

As mentioned previously, the application can be used as a preparedness tool by varying the parameters and executing replications, and also as a response tool if connected to input data in real time as a digital twin application.

¹Work done with the participation of students from the Engineering School ISIMA of Clermont-Ferrand: M. Bertoni and D. Selimovic

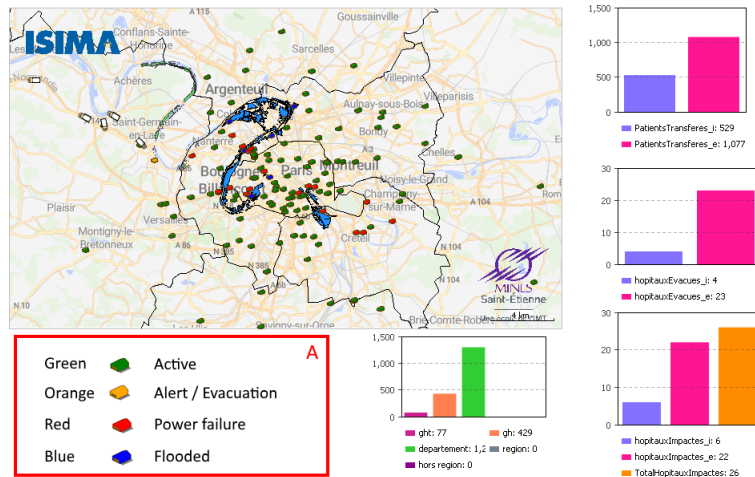


Figure 14: Simulation Manager

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