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HEALTH CARE EMERGENCY PLAN MODELING AND SIMULATION IN CASE OF MAJOR FLOOD

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ABSTRACT

Health care system is one of the most critical units in case of disasters. Floods cause an increase of emergency patient flow that may overwhelm hospital resources. In this paper, we present a simulation model that evaluates health care emergency plan and assesses the resilience of the Ile-de-France region in case of a major flood. We combined in the model the health care process with a Markov chain flood model. The results can be used to elaborate an optimized strategy for evacuation and transfer operations. We provide a case study on three specialties and quantify the impact of several flood scenarios on the health care system.

1 INTRODUCTION

Disasters, natural or man-made, can result in significant economic loss and human casualties. Disaster management operations consist of the reallocation of resources (e.g. health facilities, transportation) to respond to the disaster's emergency while covering the daily emergencies. One of the main difficulties in disaster management is the lack of resources (Hoard, Homer, Manley, Furbee, Haque, and Helmkamp 2005), and understanding the key resources and their management is primordial to adjust their utilization during a disaster.

In most of the emergency preparedness plans, health facilities represent a key resource and must accommodate the patients resulting from a disaster (Agca 2013). However, hospitals may be themselves at risk of damage from internal or external sources generated by a disaster. For example, in the Ile-de-France region, flood risk is relatively high due the geographical position. As any disaster, flood causes an increase of emergency patients flow that may overwhelm hospital resources (Takahashi, Ishii, Kawashima, and Nakao 2007). Moreover, some hospitals in the region are at risk of submersion and damages to electricity and water coverage. The patients treated in the impacted hospitals need to be transferred to other hospitals.

Hospital evacuation is more constrained than mass evacuation due to the patients' health conditions and the necessity to relocate them in appropriate facilities. In the literature, hospital evacuation operations have been approached in different ways: project management, mathematical modeling, simulation models and hybrid models (Taaffe, Johnson, and Steinmann 2006). In disaster management, simulation models address a variety of problems (e.g. prevention, response, transportation) to evaluate several outcomes (e.g. costs, mortality) (Altay and Green 2006). Some simulation models focus directly on the building architecture (e.g. exits and staircases) that are used during evacuation (Hunt 2016).

In (Voyer, Dean, and Pickles 2016), a simulation model is developed to compare the impact of different resources on the evacuation operations. The results indicate that an increase to the transportation resources (number of ambulances or the transit rate) has a smaller benefit to evacuation than a change in the available capacity of the safe hospitals. The study in (Yi, George, Paul, and Lin 2010) focuses on the analysis of the available capacity in safe hospitals in Florida, ans estimates the absorption ability of the region in case of flood. In (Taaffe and Tayfur 2006), 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). Moreover, emergency patients' flow also varies during disasters such as flood events. However, only few studies integrate the uncertainty of disasters in the simulation models (Stilianakis, Consoli, et al. 2013). (Bankes 1993) suggests using interdisciplinary simulation models using for example meteorological or geological principles.

In France, the French White Plan (Plan Blanc) is an emergency management plan in case of a sudden increase of activity in a hospital (Chen, Guinet, and Ruiz 2015). If the increase of activity involves several hospitals, an Extended White Plan is triggered to coordinate both impacted hospitals and the hospitals receiving the evacuees. One of the main decision makers in the development and application of the Extended White Plan in a given region is the Regional Health Agency (Agence Régionale de Santé ARS).

Our aim in the project with ARS Ile-de-France is to develop a simulation model to evaluate the performance of the regional hospitals in case of a flood event.

We present in this paper a discrete event simulation model that includes two major parts:

- A health care process on a regional (macroscopic) level.
- A flood model using Markov chain to represent the flood dynamic and thus capture the dynamic variation of patients' flow.

The paper is organized as follows: first we describe the general approach and the various data used in our model. Then we detail the flood modeling and the health care process. Finally, based on a real data set, we present examples of results of the model quantified by key performance indicators.

2 GENERAL APPROACH AND INPUT DATA

The main objective of the DES model we present in this paper is to evaluate the emergency plan of the regional (Ile-de-France) health care system and assess the region's resilience in case of flood.

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 treat 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.

Therefore, to evaluate accurately the preparedness plan and the decisions before and during flood, the proposed approach (presented in Figure 1) combines a patient flow model with a dynamic flood model using Markov chains.

In this approach, two main parts are distinguished: the patient flow model and the flood model. The patient flow model is implemented in order to simulate all care pathways in all hospitals at the macroscopic level over a long horizon (one or two years); the flood model is a dynamic short term event (few days to few weeks). When the flood alert starts, health care processes are adjusted by including the flood management rules until the resorption of the flood. Such processes are considered as degraded care pathway (evacuation of the hospital and/or patients transfers). Input data (green boxes) feed the aforementioned models: hospital data (capacity per specialty, flood risk evaluation...), patient data (referred hospital, length of stay, arrival time...) and geographical data (maps of departments within the region, flooded zones...). Finally, several Key Performance Indicators (KPI) are measured (regional resilience probability, number of transfers...) as an output of the model (orange box).

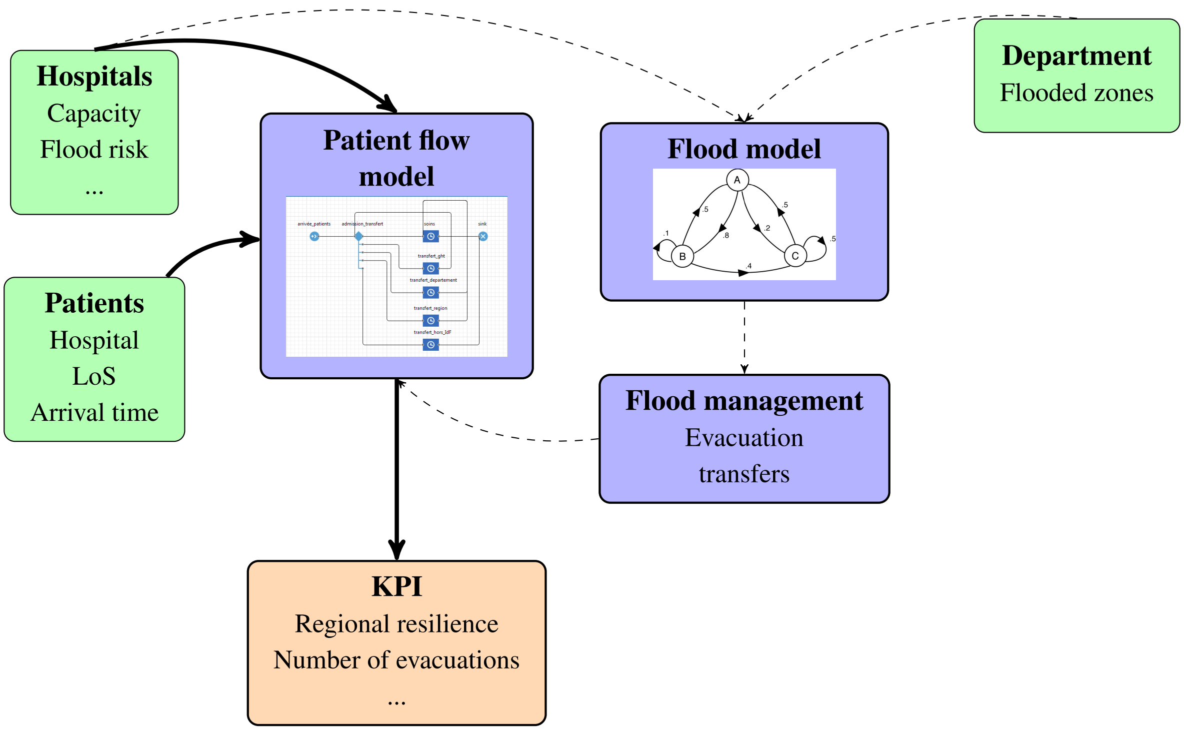

Figure 1: General approach of the flood management model.

2.1 Input Data

In this part of the model, we simulate the flow of patients on a macroscopic level without modeling their pathway inside the hospitals. Two sets of data are used as entry of this part: hospitals data and patients data.

2.1.1 Hospitals Data

The capacities of hospitals have a major role in our model as the available capacity of a non-flooded hospital can absorb the flow of patient 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. The ARS provides for each hospital in the region the capacity (number of equipped beds) for critical specialties (for example, surgery or obstetrics).

2.1.2 Patients Data

The national hospitalization database (Programme de Médicalisation des Systèmes d'Information PMSI) is an exhaustive nationwide 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.

Hospitals and patients data sets are used as the entry of the discrete event model. Basically, in this part of the model, patients arrive to hospitals with specified arrival rate to receive health care in a specialty for a given length of stay. In normal conditions, hospitals have enough capacity to cover patients needs and no delays or transfers are observed. This assumption allows us to identify the delays caused only by the flood event.

2.1.3 Flood Data

Based on the results of a hydraulic model (ALPHEE) , the Regional and Interdepartmental Directorate for Environment and Energy designed regional scenarios to estimate the impact of floods on the Ile-de-France region.

These scenarios use a set of simplified maps of flooded areas 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 2 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.

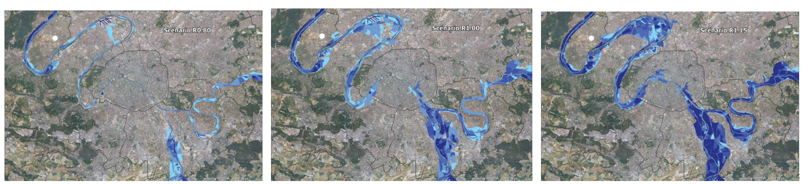

Figure 2: Three regional flood scenarios in Ile-de-France as a percentage of 1910's flood.

Although the regional scenarios help organize the emergency plans in case of flood, they have two major limitations:

1. The scenarios do not take into account the time factor, so they do not integrate the phasing of the flood.
2. In reality, the flood will not be a replica of 1910. For example, the peak of flood could be at 80% on some areas, 100% and 115% on others.

In order to correct such limitations, the flood model proposed in this paper is based on the detailed maps of regional scenarios. In addition, we combine these maps with the geographic location of hospitals to extract the list of potentially flooded hospitals for each scenario.

2.2 Flood Management Assumptions

A major assumption of the proposed model is the binary impact of the the flood on hospitals: we suppose that if a hospital is flooded, it must be evacuated and all the patients transferred. Moreover, transfer to different specialties are not allowed in our model. Flood management rules of hospitals assumed in our model are considered both during the alert period and during the flood event.

2.2.1 During the Alert Period

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 the hospitals in the region establish in our model a priority of their patients and free, if possible, a predefined percentage of their capacity. The performance of the rules applied during the alert period is measured through the three following outcomes:

- Less transferred patients in case of flood,
- better preparedness to face to the flow of emergency patients caused by the flood,
- excess capacity for patients transferred from flooded hospitals.

2.2.2 During the Flood Period

When a hospital is flooded, hospitalized patients must be transferred. Also, future scheduled patients and emergency patients are referred to other hospitals during (at least) the entire flood duration.

As the operations during emergency (especially transportation) are managed by several decision makers at the hospital level, we define a sequence of priority for the destination of transferred patients. 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 department but within the same region (state), and finally outside of the region.

If the latter option is used, the region is not autonomous anymore. In this paper, we propose a predictive model to determine the probability of a hospital group, department, and region to remain autonomous during a certain flood considering random events such as the speed and level of water and the arrival rate of patients.

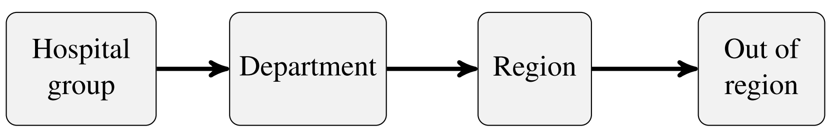

Figure 3: Sequence of evacuations and transfers.

3 THE FLOOD MODEL USING MARKOV CHAIN

The aim of this project is to elaborate a flood model that reflects a realistic flood dynamic. 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.

3.1 Features of a Flood

Starting time. In the Ile-de-France region, 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).

Moreover, patients arrival distribution varies depending on the time of the year. In our model, the starting time of the flood event is selected randomly to capture the impact of seasonality on the health care process.

Flood types. We consider two phases in a flooding event: the flood rising and 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 the ALPHEE model and validated by experts.

3.2 Flood Dynamics

In the Ile-De-France region, several measurement stations record water level and flow, 15 of which are said "reference station". For each reference station, there is a potential flooded area(Zone Inondable Potentielle ZIP). The reference stations and the associated areas are shown in Figure 4. Let Z be the set of potential flooded areas indexed by z, and S_z be the set of possible states for an area.

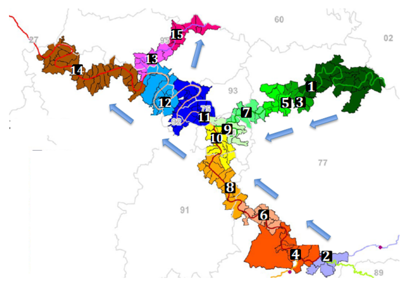

Figure 4: Water flow and the potential flooded areas associated to reference stations.

Four states are defined for each area: the first state corresponds to non-flood area; the other three states correspond to water levels relative to the 1910's reference flood and the scenarios we defined previously (*R0.8*, *R1* and *R1.15*). Notations and states are summarized in Table 1.

Table 1: Notation and definition of area states relatively to 1910's flood.

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

Space and time dynamic factors are modeled as follows: at each time unit, the flood advances in the direction of the water flow (i.e. the areas on the right (East) of Figure 4 are impacted first), and the changes of states follow that flow.

Consequently, we consider a Markovian process where each node i represents a vector $SR_i = \{s_1, .., s_{|Z|}\}$ of $|Z|$ items representing the states of all the region areas at a time period. The areas are sequenced based on the water flow represented in Figure 4.

3.2.1 Initial State

We suppose that the flood event always starts at State ST_0:

$$SR_0\left[z_i\right] = \begin{cases} 1 & \text{if } i \in \{1,2\} \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

That means, that all floods modeled start from the two extreme east regions (areas 1 and 2). Both regions are impacted by the scenario *R0.8* ($s_1 = s_2 = 1$) which represents the smallest impact considered in our model.

3.2.2 Transition Rules

A transition rule defines how the level of water is changing between two consecutive time slots (every three hours). 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 areas between two time slots. The 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. Since sudden increase (resp. decrease) in the water level are not relevant in the studied region, the value of s_z is incremented (resp. decremented) by zero or one unit. In order to keep the flow of water consistent with the slope of the ground, the water level in any downstream area z is lower (resp. upper) than the level in the upstream neighboring area z' during the previous period. Equations (1-2) and (3-4) enforce these constraints for State SR_j that follows SR_i for the increase and decrease transitions, respectively.

1. $\forall z \in Z,\ SR_j[z] \leq SR_i[z] \leq SR_j[z] + 1$
2. $\forall z, z' \in Z,\ SR_j[z] \leq SR_i[z']$
3. $\forall z \in Z,\ SR_j[z] - 1 \leq SR_i[z] \leq SR_j[z]$
4. $\forall z, z' \in Z,\ SR_j[z] \geq SR_i[z']$

All feasible transitions are equiprobable and the sum of their probabilities satisfies $\sum_{i,j|j\neq i} p_{ij} = 1 - p_{ii}$, with p_{ij} the probability to transit from node i to j.

3.3 Monte-Carlo Simulation of the Flood Dynamic Model

The proposed Markov chain model is integrated in a DES model in the following way: at each time slot, transition probabilities of the Markov models are activated. Depending on the result, the states of the areas are updated, resulting in the triggering of new management rules in the patient flow model described in the next Section.

4 HEALTH CARE PROCESS AND HOSPITAL MANAGEMENT

4.1 Petri Net Model of Patient Flow

In order to formally define the patient flow model, a generic $t-$Timed Petri net model for each hospital specialty is proposed in Figure 5. Patients arrivals are modeled using a source transition t_1. Place p_1 models the decision related to the triggering of a degraded mode for patient care in the event of a flood. If the hospital is not impacted, transition t_2 is fired and the patient stay in the hospital (the transition duration is defined by a random variable that depends on the type of stay). When the patient exits the hospital, sink transition t_4 is fired.

In the event of a flood, degraded mode is triggered and transitions t_5 (transfer to another hospital inside the same hospital group), t_6 (transfer to another hospital inside the same department), t_7 (transfer to another hospital inside the same region) or t_8 (transfer outside the region). For transition t_8, since the hosting hospital is outside the region, the patient is transferred directly to the sink transition t_4 through place p_3.

The resulting model is replicated for all hospitals and specialties of the region. As stated in Section 2, 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 then be evaluated for each hospital specialty separately.

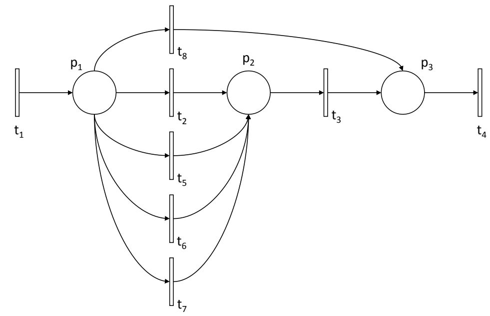

Figure 5: Generic patient flow model.

4.2 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 place p_1 is implemented using a decision node. Hospital stay (temporized transition $t3$) is implemented using a process module.

A virtual event is triggered periodically (every three hours) 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_1 is chosen accordingly to the currently used management rule and the flood state.

5 SIMULATION: NUMERICAL EXPERIMENTS

In this section, we present some results obtained with the DES model presented in the previous sections. We use several flood scenarios obtained by the Markov chain model and real data for different specialties.

5.1 Data and Scenarios

Three specialties are treated in the experiments: surgery, general medicine and obstetrics. The data collected from the hospitals in the Ile-de-France region are summarized in Table 2. Hospitals provided for each specialty their capacity, the number of patient per month, the mean length of stay. Therefore, the study is limited to the hospital specialties that gave those informations. The flood risk is evaluated for each flood scenario by mapping the hospitals locations and the flood coverage.

Table 2: Hospitals and patients data for the studied specialties.

Specialty	Number of hospitals	Maximum flooded hospitals	Total capacity	Patients per year ($\simeq$)	Mean LoS (in days)
Surgery	162	9	12,180	1,000,000	2.4
General medicine	189	11	20,601	1,748,569	3.9
Obstetrics	94	7	3,921	270,000	2.3

In these experiments, we consider 48 scenarios based on the combination of the three following parameters:

- Flood duration: We differentiate short flood events (2 to 8 days) and long flood events (8 to 20 days).
- Flood starting time (month): The flow of patients of each specialty strongly depends on the month.
- Arrival variation: Represents the additional patients flow caused by the flood event. Two cases are considered: the flow of patients remains stable or is doubled during the flood.

5.2 Performance Indicators and Results

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

Following the sequence of evacuation and transfers, Table 3 defines the list of indicators measured in this experiment.

Table 3: Key performance indicators.

$Evac$	Mean number of evacuees
T_{HG}	Mean number of patients transferred to a hospital in the same group
T_{dep}	Mean number of patients transferred to a hospital in the same department
T_{reg}	Mean number of patients transferred to a hospital within the region
$Auto$	Binary indicator that equals 1 if the region remains autonomous, 0 otherwise

We ran 100 replications per scenario. Depending on the specialty, the computing time of one replication is between 5 and 15 seconds. Results are split into three sections: the regional autonomy, the arrival variations due to the flood and the month of the flood start.

5.2.1 Regional Autonomy

For all simulated scenarios, $T_{reg} = 0$ and $Auto = 1$. This means that for the considered data, the departments are able to absorb the effects of the flood (receive the evacuees and cover the emergencies). This also implies that the set of decisions regarding the emergency operations must be coordinated within the departments (for example, the reallocation of ambulances).

5.2.2 Arrival Variation

Arrival variation has little to no impact in this experiment (Figure 6). This may be explained by the ability to absorb within each department (at most) the increased flow even when the flow of patients doubles during the flood.For the rest of the results will be presented only for $variation \times 2$ for a better readability.

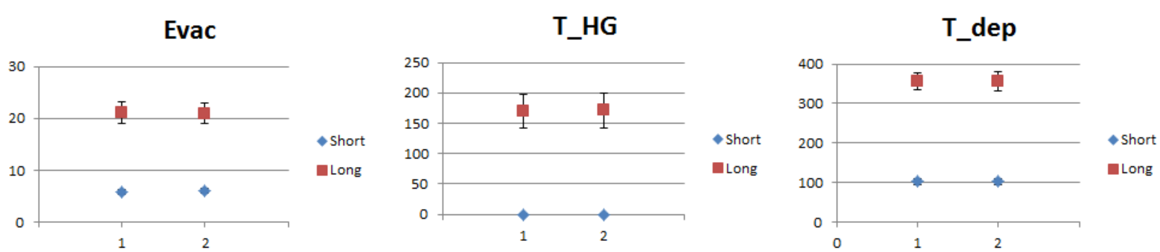

Figure 6: Examples of the impact of the arrival variation on the performance indicators.

5.2.3 Month Impact

In Figures 7, 8 and 9, the values obtained for the performance indicators $Evac$, T_{HG} and T_{reg} are given for each specialty, month and flood duration (short and long), respectively. The number of patients per month in normal conditions is also given for each specialty.

As expected the number of evacuees and transferred patients increases with the length of the flood event. For short flood events, all the areas may not be flooded depending on the random draw of transitions. Additionally, the gap between short and long event flood impact vary for each specialty based on hospitals location.

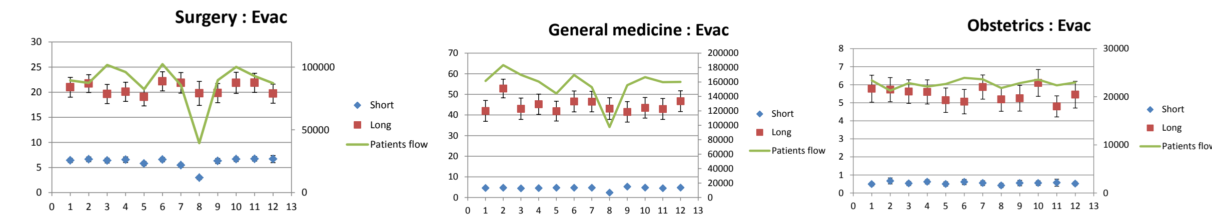

Figure 7: Mean of the number of evacuees per specialty and flood month.

The variation of *Evac* per month follow mostly the flow of arrivals of patients for each specialty. Note that each specialty is characterized by a different distribution. For example, February is the busiest month in general medicine, while the distribution of obstetrics patients is almost uniform throughout the year. At last, it is very important to note the difference of performance between the three considered specialties. This result is consonant with the patients flow in normal conditions. The most critical specialty is general medicine with a mean number of evacuees that ranges from 40 to 51 in case of a long flood.

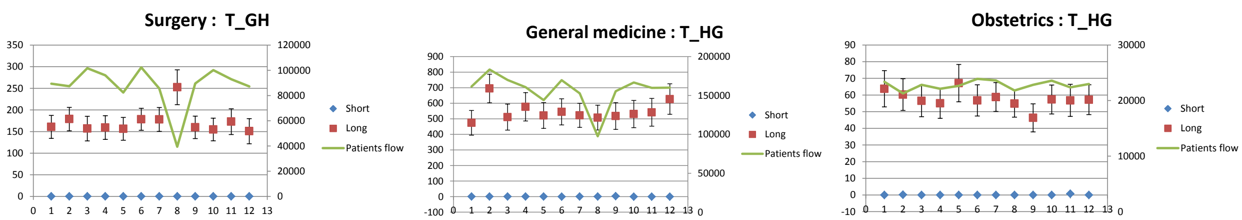

Figure 8: Mean of transferred patients in the same group of hospital per specialty and flood month.

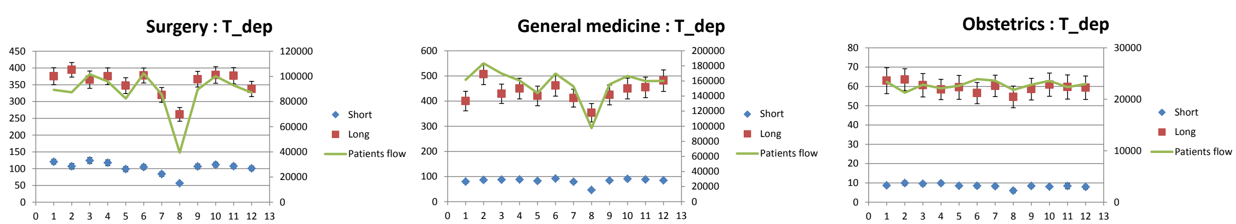

Figure 9: Mean of transferred patients in the same department per specialty and flood month.

T_{HG} and T_{dep} are correlated and must be analyzed simultaneously. For short flood events, the number of transfers within the same hospital group is equal or close to zero for all specialties (Figure 8). In the first flooded areas, the flooded hospitals are part of small group hospitals saturated by the emergency patients flow. T_{dep} follows the patients flow and is proportional to *Evac* for all specialties.

For long flood events, the smaller the patient flow the more hospital groups absorb the flood impact. For example, in the surgery case, August has the most transfers within the hospital groups (T_{HG}) while it represents the least important patient flow of the year.

Moreover, hospital groups are not uniform for all specialties. For example, if we analyze T_{dep} values, surgery seems almost as critical as general medicine during long flood events. This result is only justified by the fact that hospital groups absorb more than half of the transfers in general medicine.

6 CONCLUSION AND FUTURE WORK

We presented in this paper the work carried out with the Regional Health Agency, which aims to evaluate health care emergency plan and assess the regional resilience in case of major flood. We developed a discrete event simulation model that combines a health care process with a flood model using Markov chain. 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 the state).

In future work, additional information about patients will be added to model in order to take into account some specific needs. For example, three categories of maternity services exist in France and patients of type 3 maternity may only be transferred to the same type. Moreover, our model considers currently transfers and evacuation depending only on the hospitals capacity. However, a critical part in emergency management is patients transportation. An optimization model will be added to the simulation model (integrated or sequential) in order to plan the evacuation and transfer operations with respect to vehicles fleet capacity and routing constraints.

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