A Study Two Other Behaviours Have Been Integrated In The Modelling: The Reflex One And The Controlled One

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Abstract — *this paper proposed a new step in the modelling of the crowd dynamics in catastrophic events. Indeed, it considers three concurrent behaviours and includes the processes of transition from one behaviour to the other. Up to now the main models consist in modelling the panic which is fear behaviour, but it is not always adopted. Furthermore, panic does not necessarily last during the entire event and, on the contrary, the global behaviour of the crowd can change. In this work, two other behaviours have been integrated in the modelling: the reflex one and the controlled one. As seen in human sciences, our facsimilist show that they can influences the crowd behaviour and a return to normality.*

Keywords — *crowd dynamics, catastrophic events, facsimilist.*

I. INTRODUCTION

Nowadays, management of disasters has become a major issue, due to their huge financial and human costs. In fact, our societies, independently from their development level, are still not sufficiently prepared to a natural or anthropic catastrophe and to possible domino effects. However, there is an increasing trend concerning the number of disasters, ranking from a hundred in 1960 to 800 in 2000, and the trend is not expected to be inverted in the future, due to the population growth and densification in the risk zones. A fundamental level for reducing human vulnerability in the face of such events is the population training, to adapt their behaviours to extreme situations. In fact, during several catastrophic events, controlled and uncontrolled behaviours in individuals, small groups or crowds have been observed. These reactions depend not only on the event and its temporality (nature, unexpectedness, presence of alert), but also on the population characteristics (density, composition, preparation level). This approach permits to consider the heterogeneity of the population, but this means also high computational requirements and sometimes a difficulty in transferring the microscopic properties at a macroscopic level. At macroscopic level, the models of crowd dynamics consist in partial differential equations that describe the evolution in time and space of the density and mean velocity of the crowd flow. Finally, at mesoscopic level, between the microscopic and the macroscopic ones, we have the models that exploit the approach of the kinetic theory, through the Boltzmann or Vlahos equations, depending on the different range of interactions. The collective behaviours that have been observed in the Impact and in the destruction, zone can be classified in two main categories: The instinctive behaviours, managed by the reptilian zone of the brain that handle with the impulsive and urged behaviours. The controlled behaviours, where the prefrontal cortex adapts in a more reflexive way the reactions to an external perturbation. In the first group, we have all the behaviours of instinctive escape and fight, the panic, but also the behaviours as a sort of automaton, while in the second one we have all the persons that keep calm and self-control.

II. THE MATHEMATICAL MODEL OF DURING CATASTROPHIC EVENTS

Definition 2.1

Catastrophe:

A catastrophe is a disaster. If a wedding reception is disrupted by a fistfight between the bride and her mother-in-law, you could call the occasion a catastrophe. Catastrophe comes from a Greek word meaning “overturn’’. It originally referred to the disastrous finish of a drama, usually a tragedy.

Catastrophe event:

Something catastrophic is very harmful or disastrous. When the stock market crashes, it’s a catastrophic event for investors. This is a strong word for terrible, harmful, devastating things. Tornadoes, hurricanes, earthquakes, and tsunamis are catastrophic weather events.

Example:

This flood is a catastrophe. Licensed from iStock Photo. Noun. The definition of a catastrophe is a large, often sudden, disaster or ending. The Japan Earthquake of 2011 is an example of a catastrophe.

Catastrophic failure: Catastrophic failure is a complete, sudden, often unexpected breakdown in a machine, electronic system, computer or network. Such a breakdown may occur because of a hardware event such as a disk drive crash, memory chip failure or surge on the power line.

Catastrophic injury:

A catastrophic injury is a severe injury to the spine, spinal cord, or brain, and may also include skull or spinal fractures. This is a subset of the definition for the legal term catastrophic injury which is based on the definition used by the American Medical Association.

Catastrophe Model:

Catastrophe Modeling (also known as Cat Modeling) is the process of using computer-assisted calculations to estimate the losses that could be sustained due to a catastrophic event such as a hurricane or earthquake.

Claims:

An event is designated a Catastrophe by the industry when claims are expected to reach a certain dollar threshold, currently set at $25 million, and more than a certain number of policyholders and insurance companies are affected. Sep 19, 2017 an index used in the insurance industry to quantify the magnitude of insurance claims expected from major disasters.

Catastrophe loss:

Catastrophe loss indexes are created by third party firms that research natural disasters and work to provide estimates of the amount of losses from each catastrophe.

The mathematical model of three groups of compartmental reactions:

In this paper, we consider the human behaviors in the impact zone of a catastrophe, with a fast dynamic and no alert to the population. We suppose that the effect of surprise is total and there are no precursor signs or warnings that allow the population to adopt preventive behaviors. To give an example, there may be an earthquake or a local tsunami. We have distinguished three diverse types of behaviors in such situation. The first type consists in the reflex behaviors and concerns the reptilian brain. In our case, it corresponds to the set of instinctive behaviors except panic. This mechanism permits to react quickly, either by running away as fast as possible or by being flabbergasted and being physically unable to move in space. The second one corresponds the panic behavior. Panic has a status since, even if it is not always adopted (as, for example, during an earthquake in prepared regions as japan), This behavior is the most feared. Moreover, the extinction of collective panic is more linked to internal dynamics than to the remoteness of the danger. Thus, even if it belongs to reflex behaviors, we consider it apart due to its nature. Furthermore, in our model, the collective panic can propagate via imitation and contagion mechanisms. Finally, the third type includes all the controlled behaviors. They are governed by the prefrontal cortex, which takes over the reptilian brain. They can take different forms in a catastrophe, as, for example, evacuation, leak, containment, sheltering, research for help, pillage, theft… As for the first type, we have decided to globalize all these controlled behaviors, despite their variety. It is worth noting that the three previous behaviors do not all occur at the same time and respect a certain order. Indeed, the first behavior of an individual in the face of danger is a reflex one followed, in a second step, by controlled or panic behavior.

Formalization of the human behavior:

In this paper, we propose a SIR- based mathematical model composed of four classes, one constitutes daily behaviors, and the three others correspond to the three previous behaviors described at section. Thus, first, we did not suppose to have a class named Q composed of individuals in a daily behavior and that, during the event, no death nor birth takes place. Hence, globally the population is constant and composed by N individuals. Moreover, during the catastrophe, Q is the sum of two sub-populations:

$\boldsymbol{Q1}$(t):it designs the number of individuals with routine behaviors. Clearly, just before the catastrophic event occurs, all the population is in this state, therefore$Q1(0)$ =N,

$\boldsymbol{Q2}$(t):it designs the number of individuals who come back to normal lifestyle after the out- break of the disaster. We expect that at the end of the event, all the individuals will be in this state, thus$Q2(tend)$=N. Per section 3.1 the population during the catastrophe is decomposed into subpopulations that are represented by the following variables x(t)=number of persons with reflex behaviors, y(t)=number of persons with controlled behaviors, z(t)=number of persons with panic behavior, Since we supposed to be in presence of a sudden and unpredictable event, all the involved population will have firstly a reaction, corresponding to instinctive comportments. Thus, the routine behaviors, represented here with the variable$Q1$ (t), can only be transformed in reflex behaviors, that is in x (t). Hereafter, reflex behaviors can become controlled or panic behaviors. Since $Q2$ (t) represents the number of individual who come back to normal lifestyle, it can be alimented only by the controlled behaviors y (t). In fact, some individual needs to recover self-control to regain the everyday routine. Moreover, we suppose

that, once they have come back to normality, they maintain their habitual behaviors. Thus, the individuals in $Q2$ cannot pass in $Q1$and re-enter in the loop. Furthermore, per our psychological and geographical, during catastrophic events we have interactions and transitions between the different behaviors, as represented in Figure 1.
The exterior event, that is the catastrophe onset, is represented by forcing function Υ which can be discrete or continuous, depending on the type of the event under study. For example, an event under study. For example, an event such as a local tsunami can be modeled by a discrete function, whereas an inundation can be modeled by a continuous function since it can be announced fewer hours before its start. In our case, we supposed to be in the first situation and the Brutality and the speed of the catastrophic event is modeled through a logistic function. For considering the possible continuation or repetition of the catastrophe perception stress, the arrows labeled $s1ands2$ are added, where $s1ands2$ are supposed to be constant parameters. Once the population is in a reflex behavior, they can evolve in a controlled or panic one per the parameters $B1andB2$, respectively. γ(t) behaviors ϕ(t) instinctive behavior, managed by the reptilian zone of the brain controlled behaviors, managed by the pre-frontal cortex In the same way, a part of the controlled population can evolve to a panic are causality links behavior and reciprocally per the coefficients $c1andc2$, respectively. All the previous transaction is causality links. However, some processes of imitation and contagion exist and are modeled by the arrows labeled α, μ, δ. In the graphic, α transposes the process of imitation between x and y which is realized in both direction. This process is modeled as an epidemiological propagation and has the following form: α.$f1$ (x(t)). y(t). This modeling permits to favor the imitation in one direction, from x to y. indeed in our numerical tests, we have assumed that there must be at least 55% of reflex behaviors for that controlled individual behaviors imitate reflex ones. In the same manner, the constant δ traduces the imitation processes between x and y and is modeled by the function δ. $f2$ (x(t)). z(t). Finally, the constant μ traduces the imitation processes between controlled and panic individual's behavior, knowing that the imitation is essentially in the sense panic towards controlled individual's behavior. It modeled by the term μ. g(y(t)). z(t). From the graphical modeling in Figure 1, the mathematical model is deduced:

$$dx\ dt = \gamma(t)Q1(t)(1 - x(t)\ xm\ ) - (B1 + B2)x(t) + \alpha f1(x(t))y(t) + \delta f2(x(t))z(t) + s1y(t) + s2z(t),$$
$$dy\ dt = B1x(t) - \alpha f1(x(t))y(t) + C1z(t) - s1y(t) - C2y(t) - \varphi(t)y(t)(1 - Q2(t)\ Q2m\ ) + \mu g(y(t))z,$$
$$dz\ dt = B2x(t) - s2z(t) - \delta f2(x(t))z(t) - C1z(t) + C2y(t) - \mu g(y)z,$$
$$dQ1\ dt = -\gamma(t)Q1(t)(1 - x(t)\ xm\ ),$$
$$dQ2\ dt = \varphi(t)y(t)(1 - Q2(t)\ Q2m\ )$$

Since the concerned population is supposed to be constant, that is the equality $Q1(t) + Q2(t) + x(t) + y(t) + z(t) = N\ for\ all\ t \in [O,T]$ is verified, system can be reduced to four equation and rewritten as:

$$dx\ dt = \gamma(t)Q1(t)(1 - x(t)\ xm\ ) - (B1 + B2)x(t) + \alpha f1(x(t))y(t) + \delta f2(x(t))z(t) + s1y(t) + s2z(t),$$
$$dy\ dt = B1x(t) - \alpha f1(x(t))y(t) + C1z(t) - s1y(t) - C2y(t) - \varphi(t)y(t)(1 - N - Q1(t) - x(t) - y(t) - z(t)\ Q2m\ ) + \mu g(y(t))z(t),$$
$$dz\ dt = B2x(t) - s2z(t) - \delta f2(x(t))z(t) - C1z(t) + C2y(t) - \mu g(y)z(t),$$
$$dQ1\ dt = -\gamma(t)Q1(t)(1 - x(t)\ xm\ ).$$

Human behaviors in evacuation crowd dynamics:

Human crowds as a large living system in evacuation dynamics:

The dynamics of a crowd, as already mentioned, cannot be simply confined to mechanical and deterministic causality principles. In fact, the heterogeneous behaviors of pedestrians and their social dynamics can have an important influence over the dynamics and in the strategy; they use to achieve a certain objective of their movement in interactions with other pedestrians.

This strategy is not simply an individual one, it depends on the collective one which, due to nonlocal interactions, can find a consensus toward a commonly shared strategy. This section tackles the first key problem: understanding the major features of a human crowd viewed as a "social" hence complex system. Let us now consider the assessment of the most important complexity features of a crowd viewed as a living system within the framework that our society is a complex system.

The general strategy proposed in is that the mathematical approach to modeling of living, hence complex, system should consider the features. These general considerations should be focused on the specific field of application treated in this, namely the modelling of crowds in evacuation dynamics. Evacuation dynamics shows the appearance of special stress conditions. Some stress conditions can be amplified in special venues such as lively foot-bridges.

Contributions to understand the psychology of a crowd are, selected among various ones, where stress can end up with panic and even with aggressive behaviors. Bearing all above in mind, let us give, a possible definition of how a crowd can be defined:

Ability to express a strategy:

Walkers are capable to develop specific strategies, which depend on their own state and on that of the entities in their surrounding environment. Different strategies can appear in the dynamics. Examples include pedestrians who move toward different directions, and a crowd in a public demonstration with a small group of rioters, whose aim is not the expression of a political-social opinion, but instead to create conflict with security forces.

Heterogeneity and hierarchy:

The ability to express a strategy is heterogeneously distributed, referring to both the differences in walking abilities, and to social expressions. This feature can include a possible presence of leaders, who aim to drive the crowd to their own strategy. Leaders can contribute, in evacuation dynamics, to drive walkers toward appropriate strategies including the selection of optimal routes among the available ones.

Nonlinear and nonlocal interactions:

Interactions are nonlinearly additive and involve immediate neighbors, but also distant individuals. Interactions refer both to mechanical and social dynamics and include those with the external environment and the venue, where the walkers move. A key example is given by the onset and propagation of stress conditions, which may be generated in a certain restricted area and then diffused over the whole crowd.

Microscopic to collective behaviors:

Pedestrians can communicate and develop a social dynamic. This communication can diffuse emotional state among walkers. Accordingly, they modify both strategy and dynamical rules followed in their dynamics. The output is a collective behavior which can be observed over the whole crowd.

A general overview of this approach is presented in the project, where the basic concepts of stochastic games are introduced. Applications to model crowd dynamics and social systems are proposed in for a crowd in unbounded domain, and for dynamics in complex venues. Once a model has been derived, its validation needs to be performed.

The validation of models basically means verifying their ability to reproduce empirical data, detected in steady flow conditions at a quantitative level and to depict emerging behaviors at a qualitative level in unsteady conditions. This agreement must be achieved for a suitable choice of the model's parameters.

The validation of crowd models is a challenging topic that, with a few exceptions such as and a few others, is poorly treated in the literature. The amount of empirical data available is quite limited for developing a detailed validation process. Hence, a strategy should be elaborated to exploit the existing data at the best of the panorama they offer.

An additional difficulty is that the greatest part of empirical data sets is available at the macroscopic scale, while the modeling process needs a detailed understanding of the dynamics at the microscopic scale. Quantitative validation of models will reproduce the features captured empirically using velocity and flux diagrams that are measured against speed in steady flow conditions.

Qualitatively, emerging behaviors observed evacuation time is stressful conditions; need to be reproduced in the model output. Bearing all above in mind, let us define more precisely the validation strategy according to the following milestones concerning the performance of a model. Ability to capture the complexity features of a crowd viewed as a living, hence complex, system. Models should reproduce, even at a quantitative level, the velocity and fundamental diagrams of crowd traffic.

Moreover, features such as the transition from free to congested flow, with possible changes to interaction rules, should be caught at least at a qualitative level. Models should consider that environmental conditions can determine different observable dynamics. Models should qualitatively reproduce emerging behaviors. They should catch the transition from small to large deviations by means of properly identified parameters.

Critical Analysis:

The overview on crowd dynamics and safety problems presented in this project has shown that the literature in the field can give valuable contribution to the crisis management of human crowds in evacuation situation. However, it is worth stressing that several problems are still open and need further research activity.

Some perspectives can be given out of said overview and critical analysis. Without claim of completeness, some remarks can be referred to the three sentences quoted. The importance of understanding human behavior in crowds is undisputed. It is required for ensuring that proper support can be given to crowd managers in preparation and during crowd event.

This important hint indicates that understanding social and dynamical behaviors of a crowd is the necessary basis for any decision process related to safety. The problems consist not only of acquiring this type of information, but also support practical decision making. Our project has put in evidence that any approach should consider the crowd as a living, hence complex, system. Hence, understanding the complexity features of human crowd is very important also in designing computational models. Crowd management involves accessing and interpreting a wide variety of information sources,

Predicting crowd behaviors as well as deciding the use of a range of possible, highly context-dependent intervention mechanisms: indeed, a broad variety of information sources is very important here we simply stress that the design of the predictive engine can contribute to select the available information. However, data to be inserted should be properly assessed. Otherwise, the information can be even misleading.

The authors agree that decision support can be aided by the inclusion of relevant, validated and practical use of crowd models and the existing literature on crowd modeling can only partially support crisis management. As shown in this, further parameters could be modeled to increase the relevance and accuracy of models used for this purpose. Indeed, new modeling techniques are often required to achieve this as proposed in this project. These techniques can account for some of the identified enhancements, though we claim to have covered them exhaustively. Partially positive answer in the last issue indicates that future research activity on crowd modeling should focus on a deeper integration of psychological and behavioral features in models. This effort can be supported by empirical data on crowd detection specifically related to social behaviors.

III. CALIBRATION OF THE MODEL OF HUMAN BEHAVIOR

Definition 3.1:

Human behaviour:

Human behaviour is studied by the specialized academic disciplines of psychiatry, psychology, social work, sociology, economics, and anthropology. Behaviour is impacted by certain traits everyone has. The traits vary from person to person and can produce different Behaviour from each person.

Social work theories are general explanations that are supported by evidence obtained through the scientific method. A theory may explain human behaviour.

Organizational Behaviour:

In the business world, today, Organizational Behaviour is an essential tool for managing effective teams and it helps to understanding and predicts human behaviour in an organization. It studies on how organizations can be structures more accurately, and how several events in their outside situations effect organizations.

3.2 populations adopting the percentages of a certain type of behaviour:

The several types of human behaviours described previously can manifest in variable proportions, in function of the considered catastrophe, the suddenness of the threat, the composition of the group, the individual aptitudes for understanding the danger and the knowledge of the environment.

Moreover, considers that in most of the catastrophe, ‘’15% of individuals manifest obvious pathological reactions, 15% keep their cool and 70% manifest an apparently calm behaviour but answer in fact to a certain degree of emotional side ration and loss of initiative which reports to a pathological register”.
These percentages must be modulated per the different parameters of our model, which leads us to consider:
$x(t)$=50 to 75% of the population $y(t)$=12 to 25% of the population $z(t)$=12 to 25% of the population
At our knowledge, no data are available for quantifying transition mechanisms from one state to another.

3.3 The duration of the behaviour:

The three different reactions have different duration. The duration of the reflex and panic behaviours varies from few minutes to our hour. Most of the time, these two types of behaviour do not exceed 15 minutes. However, for the first one, it may take longer especially if it corresponds to a delay of evacuation in a disaster area. In this case, support and research behaviors for relatives and victims gradually appear. For the second one, the collective panic behaviours resolve generally spontaneously. However, sometimes, an external intervention permits to the panic population $z(t)$ to come back to an automate behaviour $x(t)$, before adopting a controlled behaviour $y(t)$. In general, the duration of the uncontrolled behaviour $x(t)+y(t)$ does not last more than 1h30. In this model, we suppose that an individual cannot stay 1 hour in a reflex behaviour and another hour in a panic state. The duration of the controlled behaviour $y(t)$ varies from few minutes to fewer hours, per the intervention of the emergency response. The choice of the parameters will be done to find these data.

3.4 Calibration of model parameters:

This section reports in the calibration procedure used for determining the best value of parameters in the RL and winner models. For the RL model, the model parameters that need to be determined includes: α (or

ATF), ATC, and W. The best value of these three parameters was determined using the four calibration functions for Environment Inflow in the DSF task: L+, L-, NL+ and NL-.

To calibrate these parameters in the RL model, a constraint-based optimization procedure was followed which could be defined as Objective: Min {Sum of average RMSE Discrepancy in 4 Environment Inflow Functions L+, L-, NL+, and NL-} subject to, $0 \leqslant \alpha \leqslant 1$, {dimensionless} $0 \leqslant ATC \leqslant 100$, {trial} $0 \leqslant W \leqslant 1$,{dimensionless} Thus, the aim of the optimization procedure is to find the best values of the three parameters(above) such that it would result in the minimum value for the sum of the average RMSE over the Discrepancy between the RL model's data and human data across the four calibration functions. The average RMSE for Discrepancy is evaluated by using average Discrepancy across 100 trials in the DSF task, where the Discrepancy is averaged over all human and model participants for each of the 100 trial points. The number of model participants used was the same as the number of human participants in four different calibration functions {these were reported in the DSF task section for different function above}. The lower bound value of the three constraints is defined to be 0, as these parameters cannot be negative {and a negative value will be meaningless}. The upper bound value of ATC constraints is defined to be 100, as that is the maximum trial value across distinct functions in the DSF task. The α and W parameters are weights in the equations of the RL model and thus these parameters can only contain real value between 0 and 1. To carry out the actual optimization, a genetic algorithm program was used. The genetic algorithm tries out different combinations of the three model parameters to minimize the RMSE between the model's average Discrepancy and the corresponding human's average Discrepancy. The best-fitting model parameters are the ones for which the RMSE in the objective function will be minimized. The stopping rule for the algorithm in the RL model's optimization was set act 10000 trials of different combinations of the three parameters. This stopping rule value is extremely large and thus ensures a very high level of confidence in the optimized parameter values obtained {for more details on the genetic algorithm program}. The parameters of the winner model were already optimized using the four calibration functions, L+, L-, NL+, and NL-, by its creator at the time of submitting the model to the MCC. Thus, the winner model was used "as is'' to compare it to the calibrated RL model in the DSF task. The next section reports the best values of the parameters from the RL and winner models.

3.5 Calibration results:

The optimization of the RL model resulted in a low value of 10.55 gallons for the RMSE averaged across the four calibration functions. The individual RMSE and R2 in different calibration functions. The best values of these parameters seem to have an interesting effect.

The ATC value is about 3 trials in the RL model and this ATC value is much closer to the two-trial value that was also found in human data of the collected verbal protocol in the NL+ function (reported above). Thus, the RL model appears to provide a close representation to the observations found in human data.

Furthermore, the value of α in the RL model is about half of 0.5. Thus, the model predominantly bases its User Inflow and User Outflow decisions on the past experiences of the Environment Net Flow values rather than on the last trial's (or most recent) Environment Net Flow value. Furthermore, the value of W parameter is very high and close to 1.0.

This means that the model understands the dynamics of the DSF task (a non-zero Environment Inflow and a zero Environment Outflow in different calibration functions) and like human participants in verbal protocols, it primarily uses the User Outflow than the User Inflow.

Thus, the model tries to bring the stock level back to the goal by removing the water stock that is added by the Environment Inflow in each trial. The similarity between the behaviour of the model and human data highlight the fact that the RL model is a plausible account of human behaviour in the DSF task.

3.6 Behaviour Duration- Description, Procedures, & Example:

If you are interested in measuring how long a behavior lasts you can use a duration recording method. Make sure that the behavior that you are observing has a clear beginning and a clear ending so that you can tell exactly when the behavior starts and when it finishes. You will also need some timing instrument such as a wall clock, wristwatch, or stopwatch.

Examples of behaviors that you might want to measure the length of include crying, being out of the classroom, or being in a location of the classroom. Procedures * Make sure that you have your timing instrument available prior to beginning your observation* Each time that the behaviour occurs:

Write down the time when the behaviour stopped calculate the length of time that the behaviour lasted and write it in minutes and/or seconds.

3.7 Factors influencing the human behaviours in the context of disasters:

To position us research about the state of the art in this domain, we will first precise the notion of human behaviours and the factors influencing these letters during a catastrophic event. This fast overview will permit to specify our choices both in terms of reactions to consider and parameters to integrate in the modelling. In 1936, K. Lewin (1936) formalized the human behavior © by a function of the form: C=f (P, E). This formulation indicates that the environment (E), in the broader sense of the term (i.e. physical, social cultural, spatial, temporal environment), and the characteristic of individuals (P) (i.e. physical resistance, experience, memory of past events) are parameters conditioning the reactions of populations. Relatively to the field of disasters, these parameters are:

a) Origin of the risk and anticipation of the beginning of the disaster (parameter E):

Some disasters can be anticipated and announced by different information channels (newspapers, radio, televisions…). It is often the case of hurricanes, floods, volcanic eruption. However, other disasters arrive by surprise as earthquakes and nuclear explosions or, in another domain, terrorist actions.

In the first case, we observe controlled behaviours (Baumann and Sims 1974; George and Gammon, 2011) since the authority's actions allow the population to be prepared in front of the risk (organized evacuation, consideration of the potential effects of the disaster)

Whereas in the second case, because of the effect of surprise and fear, reactions are more instinctive (Laborite, 1994), immediate and automatic (side ration, leak for example during non-anticipated auto-evacuation) at least in the first time in stands of a disaster (Procinolol et al., 2015).

b) Areas of the disaster (Parameter E)

Human behaviours depend also on the area of the catastrophe in which the population is located (Crocq, 1994). The affected area is usually divided in four types of zoning: the impact zone, where the material destruction zone,

Where the material damages are very important but where the number of injured people is less, and the social organization is very perturbed; and external zones which are generally less impacted by the disaster.

c) Specificities of the impacted zone (Parameter E)

The human behaviours and the associated displacements are generally guided by the territory and the alternatives that it offers particularly for the evacuation or leak, the accessibility of temporary shelters. One can name some non-exhaustive elements that affect the behavior reactions: the presence of open spaces or buildings permitting to ensure the security of populations,

The number and the position of exits (Helbing et al., 2000; Henein and White, 2005), the identification of arrow evacuation exits, the morphology of networks and the state of the communication infrastructures (Nabaa et al., 2009).

d) Characteristics of individuals (Parameter P) and density of population (Parameter E)

The behaviours vary also with the physical factors of individuals (age, agility), their learnings and experiences (culture of risk), their knowledge about the place, the individual's motivations (join or save his family members, to become a hero….) but also the local perception of the environment (Wijermans, 2007). Indeed, without any consideration of the risk, most of individuals are influenced by the density of population (E). This density, which increases when the crowd is being formed, makes the situation more dangerous (i.e. reduction of the choices for the individual displacements, increasing of interactions between individuals and their neighbours) and can lead, for example, to extreme situations of trampling and suffocation. The origin of the risk, the anticipation of the beginning of the catastrophe and the spatial zoning are factors that are considered in the construction of the mathematical model. At this stage of the modeling, we have decided to integrate general parameters, that is parameters not specific to an area or to social, economic or cultural characteristics as age, sex, cultural area, level of income or wealth Indeed, the latter do not play key role during the catastrophe but rather before and after the catastrophe (Baumann and Sims,)

3.8 Prevention of catastrophe events:

Most people think of "near misses" as harrowing close calls that could have been a lot worse- when a fire-fighter escapes a burning building moment before it collapses, or when a tornado miraculously veers away from a town in its path. Events like these are rare narrow escape that leave us shaken and looking for lessons.

But there's another class of near misses, ones that are much more common and pernicious. These are the often-unremarked small failures that permeate day-today business but cause no immediate harm. people are hardwired to misinterpret or ignore the warnings embedded in these failures, and so they often go unexamined or, perversely, are signs that systems are resilient, and things are going well.

Yet these seemingly innocuous events are often harbingers; if conditions shift slightly, or if luck does not intervene, a crisis erupts. Consider the BP Gulf oil rig disaster. As a case study in the anatomy of near misses and the consequences of misreading them, it's close to perfect. In April 2010, as gas blowout occurred during the cementing of the Deepwater Horizon well.

The blowout ignited, killing 11 people, sinking the rig, and triggering a massive underwater spill that would take months to contain. Numerous poor decisions and dangerous conditions contributed to the disaster: Drillers had used too few centralizers to position the pipe the lubricating "drilling mud" was removed too early, managers had misinterpreted vital test results that would have confirmed that hydrocarbons were seeping from the well.

In addition, BP relied on an older version of a complex fail-safe device called a blowout preventer that had a notoriously spotty track record. Why did Transocean (the rig's owner), BP executives, rig managers, and drilling crew overlook the warning signs, even though the well had been plagued by technical problems all along (crew members called it "the well from hell")?

We believe that the stakeholders were Lulled into complacency by a catalog of previous near misses in the industry successful outcomes in which luck played a key role in averting disaster. Increasing numbers of ultradeep wells were being drilled, but significant oil spills or fatalities were extremely rare. And many Gulf of Mexico wells had suffered minor blowouts during cementing (dozens of them in the past two decades);

However, in each case chance factors-favorable wind direction, no one welding near the leak at the time, for instance-helped prevent an explosion. Each near miss, rather than raise alarms and prompt investigations, was taken as an indication that existing methods and safety procedures worked. For the past seven years, we have studied near misses in dozens of companies across industries from telecommunications to automobiles, at NASA, and in lab simulations.

Our research reveals a pattern: Multiple near misses preceded (and foreshadowed) every disaster and business crisis we studied, and most of the misses were ignored or misread. Our work also shows that cognitive biases conspire to blind managers to the near misses. Two cloud our judgment. The first is "normalization of deviance," the tendency over time to accept anomalies-particularly risky ones-as normal.

Think of the growing comfort a worker might feel with using a ladder with a broken rung; the more times he climbs the dangerous ladder without incident, the safer he feels it is. For an organization, such normalization can be catastrophic. Columbia University sociologist Diane Vaughan coined the phrase in her book The Challenger Launch Decision to describe the organizational behaviors that allowed a glaring mechanical anomaly on the space shuttle to gradually be viewed as a normal flight risk-dooming its crew.

The second cognitive error is the so-called outcome bias. When people observe successful outcomes, they tend to focus on the results more than on the (often unseen) complex processes that led to them.

IV. CONCLUSIONS

This paper introduces a new step in the modelling of the crowd dynamics in catastrophic events. Indeed, it considers three concurrent behaviours and includes the processes of transition from one behaviour to the other. Up to now the main models consist in modelling the panic which is fear behaviour, but it is not always adopted. Furthermore, panic does not necessarily last during the entire event and, on the contrary, the global behaviour of the crowd can change. In this work, two other behaviours have been integrated in the modelling: the reflex one and the controlled one. As seen in human sciences, our facsimilist show that they can influences the crowd behaviour and a return to normality. The next step of this work will consist in doing a mathematical study of this model and integrating it in a diffusion process.

REFERENCES

[1] Bellomo. N and Dogb' e.C. On the modeling of traffic and crowds: A survey of models, speculations, and perspectives. SIAM review, 53(3):409– 463, 2011.

[2] Boyd.S.T. R´ eactions psychologiques des victimes de catastrophes. South african Medicine Jal, 60:744–748, 1981.

[3] Crocq. L. La psychologie des catastrophes et les bless´ es psychiques. Noto R. M´ edecine de catastrophe, Paris, Milan, Barscelone, Masson, 1994.

[4] Crocq.L. Les paniques collectives. Paris: Odile Jacob, 2013

[5] Dubos-Paillard.E Provitolo.D and Mu¨ller.J. P Emer- gent human behaviour during a disaster: thematic versus complex systems approaches. In EPNACS 2011 within European Conference of Complex System, Septembre 2011.

[6] Provitolo.D Dauphin´e.A Risques et catastrophes. Ob- server, spatialiser, comprendre, g´ erer. Paris: Armand Colin, 2013.

[7] Venel. J Maury.B A mathematical framework for a crowd motion model. Acad.C. R Sci. Paris, 346:1245– 1250, 2008.