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MODELING NEWS DISSEMINATION ON NUCLEAR ISSUES

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ABSTRACT

Using a modified epidemiological model, the dissemination of news by media agents after the occurrence of large scale disasters was studied. A modified compartmented model was developed in a previous paper presented at INAC 2007. There it used to study to the Chernobyl's nuclear accident (1986) and the Concorde airplane crash (2000). Now the model has been applied to a larger and more diverse group of events - nuclear, non-nuclear and naturally caused disasters. To be comprehensive, old and recent events from various regions of the world were selected. A more robust news repository was used, and improved search techniques were developed to ensure that the scripts would not count false positive news. The same model was used but with improved non-linear embedded simulation optimization algorithms to generate the parameters of interest for our model. Individual parameters and some specific combination of them allow some interesting perceptions on how the nature of the accident / disaster gives rise to different profiles of growth and decay of the news. In our studies events involving nuclear causes generate news repercussion with more explosive / robust surge profiles and longer decaying tails than those of other natures. As a consequence of these differences, public opinion and policy makers are also much more sensitive to some issues than to others. The model, through its epidemiological parameters, shows in quantitative manner how “nervous” the media content generators are with respect to nuclear installations and how resilient this negative feelings about nuclear is.

1. INTRODUCTION

News on high impact subjects as climate changing, global warming, or major disasters, be them of natural causes or not, always grab people's attention. This makes plausible the conjecture that this interaction is responsible for shaping up an important part of our collective common sense. In a previous work, an adapted epidemiological model was used to study the magnitude and the longevity of the repercussion, on the international media, of two accidents - the Chernobyl Nuclear accident, Ukraine (1986) and the crash of the Concorde airplane near Paris (2000). Unfortunately that research could not be extended or deepened using the original news database [1] because of an inconsistency found in the news archival methodology. The repository owner [2] changed the way news were indexed and archived making unreliable the information on the news publishing date and therefore unsuitable for the research's purpose. Three years later, another repository [3] was found with adequate depth and breadth characteristics and accurate dating procedures. The studies were restarted, using a larger and more diverse group of events: for the present work old and recent events were chosen, in several regions of the world: Bhopal (1984), Chernobyl (1986), Deepwater Horizon's rig (2010), Haiti's earthquake (2010), Japan's earthquake (2011) and Fukushima/Daiichi nuclear plants events (2011). This paper is divided in six sections. Following the Introduction, a summary of the pertinent literature is presented; followed by problem formulation and model description. Next there are the sections on data collection and treatment, results and discussions as well as the conclusions.

2. THE LITERATURE AND CLUES FOR OUR MODEL

The public acceptance of nuclear projects became, notably since the eighties, object of special attention from managers and scientists. Nowadays, “it is consensus that the public participation on the decision process is essential to success of a new project” [5]. Indeed, great industrial accidents at the end of seventies and at the eighties have conducted people to have interest on debating the benefits face the risks of complex technologies, like nuclear power production. Sauer and Oliveira [6] pointed that disasters like the ones occurred at Three Mile Island (1979), Bhopal (1984), Chernobyl (1986), the explosion of the space shuttle Challenger (1986) and the Piper Alpha accident (1988) have promoted public opinion's discredit on the government and industry's technical and political competence on securely managing the process related to highly impacting technologies. However, it appears that public opinion perceives risk in a different way than experts. “The divergences between public and experts on what an acceptable risk is have promoted the study about two important aspects of risk management: the public risk perception and the risk communication” [5]. It is reasonable that, for different individuals or different social groups, risk has different meanings. And the media plays a single relevant role in this context: it is an important risk information communicator. Wåhlberg and Sjöberg [7] concluded that media really influences our risk perception, although it is only one factor among many others. But it is a somewhat biased factor, once media tends to focus on dramatic, controversial events that cause social upheaval.

News about industrial processes not rarely are more obscuring than enlightening to people searching for information about their associated risks: many news “are concentrated on potentially catastrophic effects and on risks of diseases, deaths and injury for next generations” [6]. The most fundamental ways media contributes to distort the public risk perception are the numbers and the spectacular tone of news concerning some subjects [7]. This fact has motivated many authors to search for a quantitative model for diffusion of news concerning a risk agent. We looked for such models on the famous book entitled Diffusion of Innovations, published in 1954, Everett M. Rogers [8] presents some approaches on modeling the diffusion of novelties. His research and work became widely accepted in communications and technology adoption studies. On the other hand, the presented models make assumptions that are not applicable to news dissemination. In 1972, G. R. Funkhouser [9] published Predicting The Diffusion of Information to Mass Audiences, whereupon he modeled diffusion of information trough probabilistic approaches. Stochastic process based tools were used by Karmeshu & Pathria [10] and Allen [11] to construct models to diffusion of information. Although interesting and useful, these models didn't fit our needs. Dodds and Watts [12] developed a generalized model for social contagion, based on epidemiological models.

A paper of Bettencourt, Cintrón-Arias, Kaiser and Castillo-Chávez [13], entitled *The power of a good idea: quantitative modeling of the spread of ideas from epidemiological models*, has hinted the great potential of epidemiological compartmented models to deal with diffusion of news. We have so created a modified epidemiological model for news generation, and its construction and application to two big industrial disasters was presented to the 2007 International Nuclear Atlantic Conference – INAC 2007 [15]. In 2009, Leskovec, Backstrom and Kleinberg [14] have developed a framework for tracking memes on news media, and have used such tool to make a representation of the news cycle; at their paper, they indicate that "one can give an argument for the characteristic shape of thread volume (…) through an approximation using differential equations" [14] (Note: each thread consists of all news articles and blog posts containing a textual variant of a particular quoted phrase). These finds and arguments reinforce our previous finds that a conveniently modified epidemiological model, based on ordinary differential equations, is able to justify the thread shape that they have found. This paper adds some confirmation of the conjecture by [14] and is also a natural outspread of the one we have presented at INAC 2007 [15]. So to a certain extent, our deterministic approach to model news generation seems to constitute an innovative approach to this issue.

3. PROBLEM FORMULATION AND MODEL DESCRIPTION

It seems appealing to apply an epidemiological model to the *news* population, once the available evidences were precisely the amount of published news about each catastrophe. However, there is an immediate problem concerning this approach - news on newspapers and magazines, once they are published, they do not change, so they cannot undergo state transitions. On the other hand journalists can change their state of willingness to produce news about a subject. So the question was: would it be possible to assess information about this population from available data about published news? Assuming, *a priori*, yes, the search for an appropriate epidemiological model for the *journalists* population was elaborated. Such model should describe the possible states for the members of the population and should also describe the transitions between these states.

3.1 Compartmental Epidemiological Model for News Dissemination

Once the accident in question happens, journalists producing news about the accident are considered as *influenced* (state *I*). Those not publishing – yet – are considered as *susceptible* (state *S*). Only these two states are considered in the model, a simple epidemiological model – the *SIS* model. In fact there is no need to consider different states for other situations, like the *incubation period (state E*), *recovered individuals* (state *R*) and *non-interested (or immune) individuals* (*state Z*), for example. It is assumed that journalists that have never yet published on subjects related to the accident can still do it at any time – in other words, it is conservatively assumed that no one is immune. Also journalists that have stopped writing about it, can still publish on that subject after a while – so there is no need to consider of the immunized recovered ones. Finally, there is no reason to distinguish between *susceptible individuals* (*S*) and those in the *incubation period* (*E*), once every non-influenced are permanently exposed, because journalists are always exposed to news and direct contact with their colleagues.

The total of the population of journalists is called *J*; so, we get $J = I + S$. The standard *SIS* epidemiological model is set by the following equations:

$$\frac{d}{dt}S = -fS\frac{I}{J} + \mu I \quad (3.1)$$

$$\frac{d}{dt}I = fS\frac{I}{J} - \mu I \quad (3.2)$$

where *J* is the total of individuals, and is always constant in our model; *f* is the influence rate, and assumes always non-negative values and, when multiplied by *I/J*, it becomes the influence probability; and μ is the recovery rate, also assuming only non-negative values. *S*, *I* and *J* are, obviously, time functions.

It is appropriate to note that there is no reason for *f* to be constant. It is reasonable to expect the influence rate to decrease over time, once gradually readers' interest decreases and so the press give less and less space to news on the event. Therefore the rate at which journalists become influenced should likewise decrease. To be consistent the model will treat *f* as a *function of time*. It's natural to think of a function that has a *peak* soon after the event and decays with time until it remains small and has little variation. The $F = f \,.\, (I / J)$ corresponds to the *probability of a journalist to become influenced after being exposed.*

$$F := \begin{cases} \left\{R_0 + R_1 \exp\left[-\beta(t-t_0)\right]\right\}\dfrac{I}{J}, & \text{for } t \geq t_0 \\ 0, & \text{otherwise} \end{cases} \quad (3.3)$$

Table 1. Parameters of interest of the function *F* – probability of publishing influenced news after being exposed to this type of news.

R_0	Coefficient of the long-term news persistence of the event
R_1	Coefficient of the news outbreak of the event
β	Decay constant of the news outbreak of the event

However the differential equations that rule the state transitions of our system depends so far on functions *S*, *I* and *J*, which refer, respectively, to the number of *susceptible*, *influenced* and *all* journalists at a given moment. All these variables refer to data that is not available, for this reason some transformation should be made in the variables.

Some plausible hypotheses have to be made to relate the above mentioned quantities with the ones for which data is available. Let the number of news that *cites* the accident published at time *t* be denoted by *Q(t)*; the number of news that *don't cite* the accident published at time *t* by *P(t)*; and the *total* of published news at time *t* came to be denoted by *N(t)*. It's obvious that

$N = Q + P$ holds. Thereafter let ψ be the average productivity of the journalists – in other words, the mean number of news a journalist publishes in one day. Indeed it's reasonable to think ψ shouldn't vary when the studied time period is not too long. Then the following equations are valid to relate the *number of news* – citing and not citing the accident – and the *population of journalists*:

$$S(t) = \psi P(t); \quad I(t) = \psi Q(t); \quad J(t) = \psi N(t) \tag{3.4}$$

Functions are then normalized with respect to their values at time $t_0 = 0$; this day corresponds to the first day the news on the event appear. Adopting the notation $S_0 := S(0)$, $I_0 := I(0)$, $J_0 := J(0)$, the following definitions can be introduced:

$$\hat{S}(t) := \frac{S(t)}{S_0} = \frac{P(t)}{P_0}; \; \hat{I}(t) := \frac{I(t)}{I_0} = \frac{Q(t)}{Q_0}; \; \hat{J}(t) := \frac{J(t)}{J_0} = \frac{N(t)}{N_0} \tag{3.5}$$

This normalization brings, for example, the following ease: being the population J considered constant over the observation period, we get *$\hat{J}(t)$ constant equal to 1*. Therefore we have, so far, an epidemiological model defined by the following equation system:

$$\frac{d}{dt}S = -FS + \mu I \tag{3.6}$$

$$\frac{d}{dt}I = FS - \mu I \tag{3.7}$$

Dividing (3.6) by S_0 and (3.7) by I_0 we have:

$$\frac{d}{dt}\hat{S} = -F\hat{S} + \mu\frac{I}{S_0} \tag{3.8}$$

$$\frac{d}{dt}\hat{I} = F\frac{S}{I_0} - \mu\hat{I} \tag{3.9}$$

Let's attempt, first, to the equation (3.9). Since $\hat{I}$ is a normalized function, it would be interesting to write the equation only in terms of normalized functions. Of course, by the definition of $\hat{S}$, we have

$$S = \hat{S}S_0$$

So, one can write equation (3.9) as follows:

$$\frac{d}{dt}\hat{I} = F\frac{\hat{S}S_0}{I_0} - \mu\hat{I} \tag{3.10}$$

Once $P_0 = \psi S_0$ and $Q_0 = \psi I_0$, the following equality holds:

$$\frac{d}{dt}\hat{I} = F\frac{\hat{S}\psi S_0}{\psi I_0} - \mu\hat{I} = F\frac{\hat{S}P_0}{Q_0} - \mu\hat{I} \tag{3.11}$$

It would be interesting this differential equation depend only on the function *Î*, once this fact would make its solution easier. So one can note that

$$\hat{S} := \frac{S}{S_0} = \frac{P}{P_0} = \frac{N-Q}{P_0} \tag{3.12}$$

As N is a constant function, $N \equiv N_0$ holds. Moreover we have $Q = \hat{I}Q_0$. So the following equality is true:

$$\hat{S} = \frac{N_0 - \hat{I}Q_0}{P_0} \tag{3.13}$$

Thus equation (3.11) can be written as follows:

$$\frac{d}{dt}\hat{I} = F\frac{N_0 - \hat{I}Q_0}{Q_0} - \mu\hat{I} = F\left(\frac{N_0}{Q_0} - \hat{I}\right) - \mu\hat{I} \tag{3.14}$$

Let us turn to expression of F. One can observe that $I / J = \psi I / \psi J = Q / N$, and using $N \equiv N_0$ and $Q = \hat{I}Q_0$, one can obtain the following formula:

$$F := \begin{cases} \left(R_0 + R_1\exp\left[-\beta(t-t_0)\right]\right)\dfrac{\hat{I}Q_0}{N_0}, & \text{for } t \geq t_0 \\ 0, & \text{otherwise} \end{cases} \tag{3.15}$$

Given this formula of F, we can finally write equation (3.14) in a such way that it depends only on *Î*. We then get a *second order Bernoulli differential equation*, which is given by the following formula:

$$\begin{aligned} \frac{d}{dt}\hat{I} &= \left(R_0 + R_1\exp\left[-\beta(t-t_o)\right]\right)\frac{\hat{I}Q_0}{N_0}\left(\frac{N_0}{Q_0} - \hat{I}\right) - \mu\hat{I} \\ &= -\left[R_0 + R_1 e^{-\beta t}\right]\frac{Q_0}{N_0}(\hat{I})^2 - \left[\mu - \left(R_0 + R_1 e^{-\beta t}\right)\right]\hat{I} \end{aligned} \tag{3.16}$$

The equation (3.16) governs, accordingly, in our model, the *quantitative variation* of *influence parcel* of the population of *journalists*. From there we'll seek to identify the parameters of interest R_0, R_1, β e μ for each case – for each industrial catastrophe. These parameters, once given the utilization of each one at the model's construction, can be interpreted as follows:

Table 2. Parameters of interest of the developed model.

R_0	Coefficient of the long-term news persistence of the event
R_1	Coefficient of the news outbreak of the event
β	Decay constant of the news outbreak of the event
μ	Decay constant of influence (recovery rate from *influenced* state)

3.2 System Behavior for Large Time Values

It's worth recalling the definition of *F* – the probability of publishing influenced news after being exposed to this type of news:

$$F := f\frac{I}{J} = \begin{cases} \left\{R_0 + R_1 \exp\left[-\beta(t-t_0)\right]\right\}\frac{I}{J}, & \text{for } t \geq t_0 \\ 0, & \text{otherwise} \end{cases} \tag{3.17}$$

$$= \begin{cases} \left\{R_0 + R_1 \exp\left[-\beta(t-t_0)\right]\right\}\frac{\hat{I}Q_0}{N_0}, & \text{for } t \geq t_0 \\ 0, & \text{otherwise} \end{cases} \tag{3.18}$$

So we are able to see the equality

$$f = R_0 + R_1 \exp\left[-\beta(t-t_o)\right] \tag{3.19}$$

involving the influence rate *f*.

When $t \to \infty$, we will get:

$$\lim_{t\to\infty} \exp\left[-\beta(t-t_o)\right] = 0 \Rightarrow \tag{3.20}$$

$$\Rightarrow \lim_{t\to\infty} (R_1)\left\{\exp\left[-\beta(t-t_o)\right]\right\} = 0 \Rightarrow \tag{3.21}$$

$$\Rightarrow \lim_{t\to\infty} f = R_0 \tag{3.22}$$

Thus, for enough large values of *t*, the influence rate *f* is arbitrarily close to R_0.

This fact sets a scenario where sometimes the system, depending on R_0, R_1, β and μ, can present an interesting growing trend of influentiation on population. In other words: some events would observe a *distal turning point* from which the proportion of influenced journalists *I* would start re-growing, once it is was declining since it peaked a few days after the disaster's occurrence. Indeed, given the equation (3.19) and the definition

$$K_0 := \frac{Q_0}{N_0} \tag{3.23}$$

we are able to write the ordinary differential equation (3.16) in the following form:

$$\frac{d}{dt}\hat{I} = - fK_0\hat{I}^2 - \mu\hat{I} + f\hat{I} \tag{3.24}$$

Such equation informs us that the function $\hat{I}$ has critical points if and only if

$$- fK_0\hat{I}^2 - \mu\hat{I} + f\hat{I} = 0 \Rightarrow \tag{3.25}$$

$$\Rightarrow (\hat{I})(- fK_0\hat{I} - \mu + f) = 0 \tag{3.26}$$

If $\hat{I} = 0$, then $\hat{I}' = 0$ and $\hat{I}$ would remain zero forever – in other words, there would not be any influenced journalist, and so a re-infection process would not happen. Thus, let's see the case on which $\hat{I} \neq 0$. In this case while

$$- fK_0\hat{I} - \mu + f = 0, \text{ then } \frac{d}{dt}\hat{I} \leqslant 0 \tag{3.27}$$

and $\hat{I}$ will be continuously approaching zero, however using equality (3.22), when t is enough large, the critical point at which $\hat{I}$ starts to increase again can be calculated as the time t for which $\hat{I}$ reaches the value

$$\hat{I} = \frac{R_0 - \mu}{R_0 K_0} \tag{3.28}$$

Therefore one can conclude that if and only if $R_0 > \mu$ the critical point can be reached, because otherwise $\hat{I}$ will reach zero at an earlier time and $\frac{d}{dt}\hat{I} \leqslant 0$ at this same point making $\hat{I} = 0$ to become a permanent condition.

For processes with $R_0 > \mu$ there will be an bounded oscillatory behavior because as soon as $\hat{I} > 0$ its derivative will become less than zero pushing it back again.

The only point to be made here is that this model has the potential to consider natural “reinfections”.

4. DATA COLLECTION AND PROCESSING

Once we have the ordinary differential equation:

$$\frac{d}{dt}\hat{I} = - \left[R_0 + R_1 e^{-\beta t}\right]\frac{Q_0}{N_0}(\hat{I})^2 - \left[\mu - \left(R_0 + R_1 e^{-\beta t}\right)\right]\hat{I} \tag{4.1}$$

our main interest is to identify the parameters R_0, R_1, β and μ that provide the best fit of equation (4.1) to the reality of the collected data from the published news. We should find a point (R_0, R_1, β, μ) in $\mathbf{R}^4$ that fit as good as possible the solution of this equation to the collected data of published news about each disaster of interest; so we should get one optimal point (R_0, R_1, β, μ) for each catastrophe.

4.1 Data Collection

Data were collected from the NewsLibrary repository [3], provided by NewsBank Inc. [4]. This has shown to be the most robust, reliable and accessible repository available on the web at this time. Indeed, in a previous work [15], we used the Google News Archive Search; but this tool has shown to replace sometimes the date on which an article was published with dates cited in the articles's body, providing too many false-positives on each search; we communicate this failure to Google, but they said it's actually not a failure, but a resource to identify the time periods that are likely to be relevant to each query. So the option for NewsLibrary repository was made. The search took place in 2011 May and June. For each disaster, we have collected the number of articles published per day, since the first day in which there were articles citing the event – *day 0* – until a certain time that was called *day W*, which depends on the case, as shown in Table 3. Thus, for each integer t, $0 \leq t \leq W$, we have obtained a number $I_R(t)$ that corresponds to the number of articles published by journalists that day. The graphs of the function $I_R(t)$ for all studied events are shown in Figure 1.

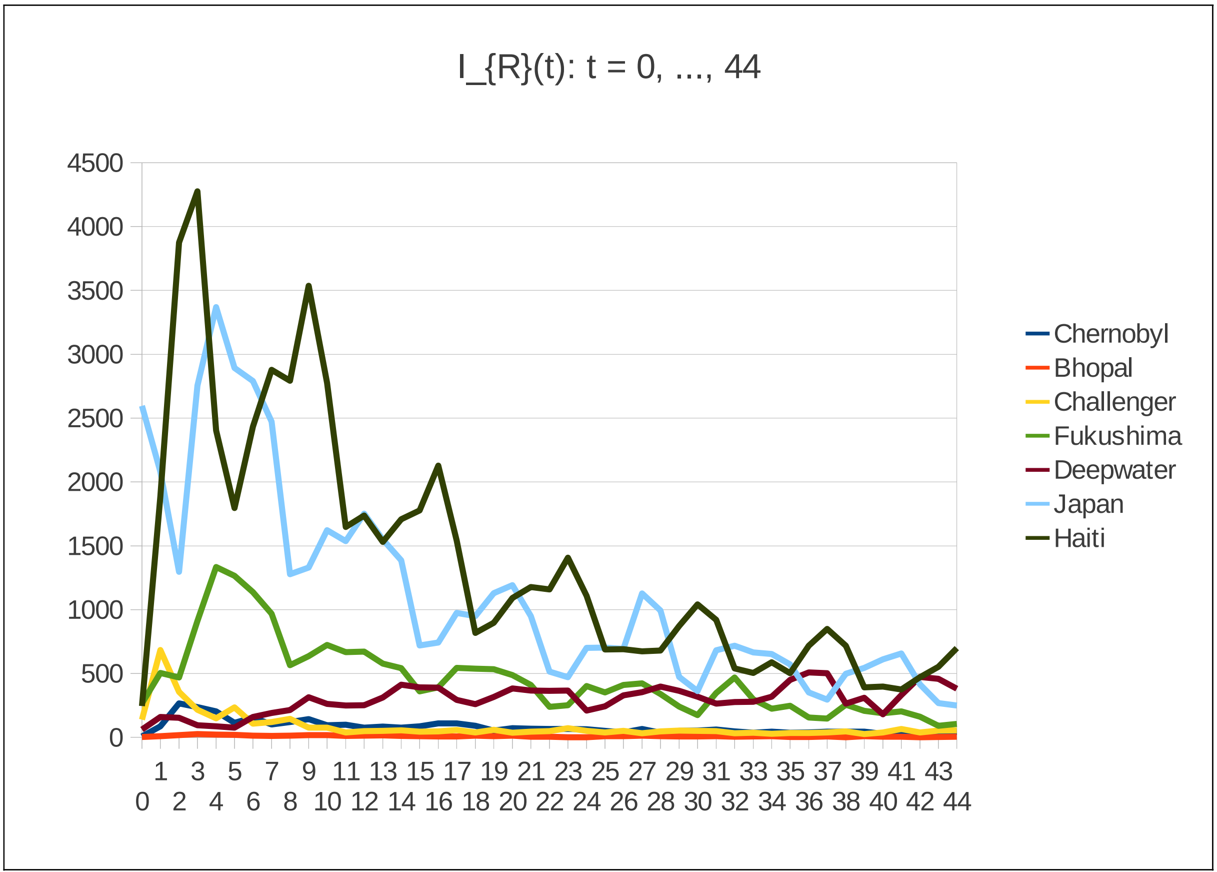

Figure 1. Graphs of the function $I_R(t)$, $t = 0, ..., 44$, for all studied events.

Table 3. Analyzed period and correspondent *day W* for all studied events.

Event	Occurrence	Analyzed period	*day W*
Chernobyl	April 26, 1896	2 years	729
Bhopal	December 3, 1984	2 years	729
Challenger	January 28, 1986	2 years	729
Fukushima	March 11, 2011	1½ month	44
Deepwater	April 20, 2010	1 year	364
Japan	March 11, 2011	1½ month	44
Haiti	January 12, 2010	1 year 3 months	454

4.2 Data Smoothing

Once the data collection for each disaster was made, the data needed to be smoothed before being approximated, because it would be approximated by a continuous function – a solution of equation (4.1).

The procedure performed to smooth the data was as follows:

a) From *day 0* to day when $I_R(t)$ reaches its maximum – *day M* – there is no change. That is, for every t, it remains the correspondent $I_R(t)$.

b) From the first days after the *day M*, we get the mean for each group of three days – one day can not belong to two different groups – and each day in this group receive as the value of $I_R(t)$ the average of their group. For example, in the case of Chernobyl, the *day M* occurs at $t = 2$. The first group of three days will so be the group for $t = 3, 4, 5$. Then, as the average of published articles per day in this group is 184, we have $I_R(3) = I_R(4) = I_R(5) = 184$. However, we used a minimum score: if the sum of the $I_R(t)$ values of the three days of the group is less than a certain C_{MIN}, then the group will now contain one more day - the next day after the last day of the group – until it reaches the minimum score. Hence, each day of the group receives as $I_R(t)$ value the average value of the group.

For each event, the correspondent minimum score C_{MIN} was set as the average of the number of published articles per day in the first half of the period taken into account (which ends at *day W*):

$$C_{MIN} = \frac{2\sum_{t=0}^{\frac{W-1}{2}} I_R(t)}{W+1} \tag{4.2}$$

We have used rounding by truncation in all operations for calculation of C_{MIN}. One should note the following: as consequence of imposition of the minimum score, the set of values *t* can assume may reduce. Since a given time *t'*, it is possible that the function $I_R(t)$ is always so small that no longer can reach minimum score untilt $t = T$. The set of values that *t* can assume now go from *0* to the last day of the last group that achieved the minimum score, which we will call the *day V*, that depends on the case, as shown in Table 4. Once the data were smoothed, it was normalized with respect to $I_R(0)$, given the very definition of the function $\hat{I}$.

4.3 Parameters Identification

Since we got the data smoothed and normalized, we proceeded to identify the parameters of interest. We have chosen to use Sequential Least Squares Programming technique [16] to find the point that minimizes our function with non-linear constraints. Indeed, we have tried many non-linear optimization methods: downhill simplex algorithm, modified Powell's method, conjugate gradient algorithm, BFGS algorithm, Newton-Conjugate Gradient method, simulated annealing, and brute force technique; a few of them provided clearly bad results – the simulation of the equation of interest using such results got quite far from reality of data. Other ones were unable to complete optimization in acceptable time. The fastest and best choice was, undoubtedly, the Sequential Least Squares algorithm.

Thus we proceeded to define the function to be minimized: let $x = (R_0, R_1, \beta, \mu)$ be as defined before. We called $I_S(x)$ the simulation – performed via the fourth-order Runge-Kutta method – of the ordinary differential equation (4.1) with the parameter set *x*, with initial conditions $t_0 = 0$, $x(t_0) = 1$ (due to the fact that $\hat{I}$ is the result of a normalization of function $I(t)$). We then called $I_S(x, t)$ the value of such simulation at time t, with t = 0, 1, 2, ..., V, where V is the number corresponding to the *day V*. The function given to the minimization algorithm was as follows:

$$E(x) = \sqrt{\sum_{t=0}^{V} \left[I_s(x,t) - I_r(t) \right]^2} \tag{4.3}$$

Table 4. C_{MIN} and consequent *day V* for all studied events.

Event	C_{MIN}	***day V***
Chernobyl	20	728
Bhopal	3	729
Challenger	26	727
Fukushima	659	42
Deepwater	217	363
Japan	1698	40
Haiti	404	449

In other words: the goal was to minimize, with respect to x, the Euclidean norm of errors between the simulation and data collected from the NewsLibrary repository. One can note that, on each iteration of the optimization process, a new simulation was performed to calculate the value of the objective function. The optimization program was executed, for all events, from the initial point *(1, 1, 1, 1)* – the canonical vector example with non-zero entries in $\mathbf{R}^4$. Table 5 contais the results obtained by performing these optmization process.

Once Table 5 was achieved, in order to assess the influence process behavior at the beggining of the analyzed period, we have calculated, for each disaster, the value $\bar{f}$ defined as the average f – the influence rate, which is a function of R_0, R_1, β and μ – for the first *40* days of the analyzed period of each event. Then we have evaluated the difference $\bar{f}-\mu$ and, in Table 6, we have sorted the events by such difference, which can indicate, if it's greater, a *stronger influence rate* opposed to a *weaker recuperation rate*. Such values would meanwhile be affected by the period in which $\bar{f}$ is evaluated. We have chosen to evalute $\bar{f}$ for the first *40* days of the analyzed period because the Japan earthquake and consequently the Fukushima accident are very recent events, and so both should not be systems with completely stable parameters. We conjecture that the calculation of $\bar{f}$ for a wider range of days would conduce Japan and Fukushima events to an approximation of their similars – respectively Haiti and Chernobyl.

We have also calculated, for each disaster, the *resilient endemic propensity* [17], which was called ε and defined as follows:

$$\varepsilon := \frac{1}{R_0 - \mu} \tag{4.4}$$

A larger ε value can point to a propensity of the event to generate an *endemic*, in other words, a self sustaining influence process that however doesn't trigger a new outbreak or epidemic. Such measure may be interpreted as the persistency capacity of the event to become the subject of new articles last long after the disaster's ocurrence – in other words, events that posses greater ε values are more resilient in the media. Table 7 shows all events ordered by calculated ε values.

Table 5. Identified parameters and objective function value for all studied events.

Event	R_0	R_1	β	μ	$E(x)$
Chernobyl	1.90161633	5.64453851	1.43305041	1.89824296	23.23606580
Bhopal	5.5789935	2.74049343	1.06153285	5.5666485	37.83153979
Challenger	4.22657173	45.71444984	8.70693565	4.2118337	2.16311943
Fukushima	19.5813878	0.81401107	0.29303129	19.53813254	2.45628832
Deepwater	5.95316998	0.13630052	0.0355955	5.9572922	16.44219916
Japan	4.95570448	0.21447007	0.18462508	4.95683549	0.86033893
Haiti	2.23739491	4.1986905	1.35348209	2.24174738	11.00282360

Table 6. Events sorted by $\bar{f}-\mu$ - *influence rate strength* - at the first *40* days of the analyzed period.

Event	$\bar{f}$	$\bar{f}-\mu$
Challenger	5.3696220759	1.1577883759
Chernobyl	2.0869456764	0.1887027164
Haiti	2.3789249099	0.1371775299
Fukushima	19.6615059701	0.1233734301
Bhopal	5.6837404353	0.1170919353
Deepwater	6.0271491561	0.0698569561
Japan	4.9874893643	0.0306538743

Table 7. Events sorted by ε – *resilient endemic propensity.*

Event	ε
Chernobyl	296.4394655789
Bhopal	81.004455245
Challenger	67.8516735276
Fukushima	23.1185756368
Haiti	-229.7545991127
Deepwater	-242.5877318532
Japan	-884.1654804107

As discussed in subsection 3.2, events that present $R_0 > \mu$ have *long-term reinfection pressure*. From Table 5 one can conclude that the only events that present $R_0 > \mu$ are Chernobyl, Bhopal, Challenger and Fukushima. It's interesting to note that the only recent disaster in this group is Fukushima – justly the only event occured in a nuclear facility. Indeed, it seems that media will faster forget the Japan earthquake itself – which unfortunately has caused too many deaths – but will not forget so fast the Fukushima nuclear power plant accident – which have not caused any death.

5. CONCLUSIONS

First it has to be noted that the research has used a news repository based in the USA and, although they collect news from all over the world, the majority of the sources come from the US. So the sample has a natural bias capturing more news items that may be of concern and interest to the US people. In general, media gives more prominence to disasters involving nuclear facilities than to other types of catastrophes. Comparing the strength of the influence rate shortly after the occurrence, Chernobyl nuclear accident ranked second and Fukushima/Daiichi ranked fourth, well ahead of Bhopal, Deepwater Horizon and Japan Earthquake itself, whose tragic consequences were of much larger proportion. Something that would not occur, should the media attention be distributed in proportion to the seriousness of the event. Given some discount due to the bias mentioned before, one can conclude that nuclear accidents don't receive always the vast majority of the attention of media agents: events that causes more commotion in public, with great appeal to emotion, or when they are associated to misfortunes of defenseless people seems to cause a even larger news outbreak, even when without involving nuclear issues. Falling into this category are the Challenger shuttle explosion – which presents the biggest R_1 (news outbreak coefficient) value – and of the devastating Haiti earthquake, the only non-nuclear events that exceed respectively Chernobyl and Fukushima in short-term influence rate.

The accident of the space shuttle caused great commotion in the U.S., as many people was watching the launch alive on TV and the explosion was terrifying to the American people. But, after Challenger, the Chernobyl accident is the most short-time striking event we have studied. In third place comes the Haiti earthquake, another very affecting event, given the poverty of the place. Moreover one can note that Japan earthquake itself presents the smallest influence rate value shortly after occurred; this is certainly due to this disaster had not caused so much commotion in public as Haiti earthquake did, once Japan is doubtless one of the richest countries in world and they have dealt very effectively with the short term consequences of it. Besides there seems to be enough human and economic resources to rebuild what was sorely destroyed.

When we look the long-term scenario for each event we also realize that disasters involving nuclear issues receive differentiated preference from media agents. Chernobyl nuclear accident presents the greatest propensity to become endemic. This seems to indicate that media will keep on coming back to the subject of nuclear accidents, much more frequently and longer than they do for others types of events. While Chernobyl has the greatest tendency of persistence on media of all catastrophes, Fukushima plant accident has the greatest propensity of endemic of all its contemporary disasters: even the Haiti earthquake is less resilient in media than Fukushima, as well as Challenger explosion is less resilient than Chernobyl. While noting that when more data is accumulated on Fukushima its respective data on tables 3 to 7 may change, it seems Fukushima is not as resilient as Chernobyl and it could even stay less resilient than the Bhopal gas tragedy. From these findings one might conclude that Fukushima event is not a “new Chernobyl event” regarding dissemination and persistence of news in the media.

Lastly it is clear that there is still much work to be conducted in modeling news dissemination by epidemiological models. The next targeted step involve implementation of our model equipped with other – maybe better – probability functions for influence rate *f*. Furthermore the use of other metrics from epidemiological sciences to help the interpretation of the modeled data has to be careful and thoroughly analyzed. An enlargement of the model to include multiple “generating facts” is currently being considered as this would be very useful to model further peaks that could be generated world conferences that are organized to discuss the event one or more years later. Finally a search is being done for other enough robust and accessible repositories of periodicals from other countries and continents. The purpose is to be able to evaluate the Country bias referred in the beginning of this section.

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REFERENCES

1. "Google News Archive Search", http://news.google.com/archivesearch (2009).
2. "Google", http://www.google.com.
3. "NewsLibrary.com - newspaper archive, clipping service - newspapers and other news sources," http://www.newslibrary.com.
4. "NewsBank, inc. A Premier Information Provider," http://www.newsbank.com.
5. F. F. T. Rocca, *A percepção de risco como subsídio para os processos de gerenciamento ambiental*, Tese de doutorado, Instituto de Pesquisas Energéticas e Nucleares (2002).
6. M. E. L. J. Sauer and J. M. Oliveira Neto, "Comunicação de risco na área nuclear," *VII Congresso Geral de Energia Nuclear – VII CGEN*, Belo Horizonte, Brazil, August 31-September 3 (1999).
7. A. Wåhlberg and L. Sjöberg, "Risk perception and the media," *Journal of Risk Research*, **3 (1)**, pp. 31-50 (2000).
8. E. M. Rogers, *Diffusion of innovations*, Free Press of Glencoe, New York, United States of America (1964).
9. G. R. Funkhouser, "Predicting the Diffusion of Information to Mass Audiences," *Journal of Mathematical Sociology*, **2**, pp. 121-130 (1972).
10. R. K. Karmeshu and R. K. Pathria, "Stochastic Evolution of a Nonlinear Model of Diffusion of Information," *Journal of Mathematical Sociology*, **7**, pp. 59-71 (1980).
11. B. Allen, "Stochastic Interactive Model for the Diffusion of Information," *Journal of Mathematical Sociology*, **8**, pp. 265-281 (1982).
12. P. S. Dodds and D. J. Watts, "A Generalized Model of Social and Biological Contagion," *Journal of Theoretical Biology*, **232**, pp. 587-604 (2005).
13. L. M. A. Bettencourt, A. Cintrón-Arias, D. I. Kaiser and C. Castilho- Chávez, "The power of a good idea: Quantitative modeling of the spread of ideas from epidemiological models", *Physica A*, **364**, pp. 513-536 (2006).
14. J. Leskovec, L. Backstrom and J. Kleinberg, "Meme-tracking and the dynamics of the news cycle," *Proceedings of the 15th ACM SIGKDD international conference on Knowledge discovery and data mining*, Paris, France, June 28-July 1 2009, pp. (2009)
15. J. S. B. Reis Junior, A. C. O. Barroso, K. Imakuma and M. O. Menezes, "News and Its Influence on The Viability of Nuclear Power Plants Deployment - A Modified Epidemiological Model for News Generation," *2007 International Nuclear Atlantic Conference - INAC 2007*, Santos, Brazil, September 30-October 5 (2007).
16. D. Kraft, "A software package for sequential quadratic programming," *Tech. Rep. DFVLR-FB 88-28*, DLR German Aerospace Center — Institute for Flight Mechanics, Koln, Germany (1988).
17. R. M. Anderson and R. M. May, *Infectious Diseases of Humans: Dynamics and Control*, Oxford Univ. Press, Oxford, England (1991).