Accelerated Virus Spread Driven by Randomness in Human Behavior

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Abstract. In this paper is demonstrated that the morphology of infection's curve is a consequence of the entropic behavior of macro-systems that are entirely dependent on the nonlinearity of social dynamics. Thus in the ongoing pandemic the so-called curve of cases would acquire an exponential morphology as consequence of the human mobility and the intensity of randomness that it exhibits still under social distancing and other types of social protection adopted in most countries along the first wave of spreading of Covid-19.

Keywords: Epidemiology · Global pandemic · Human behavior

1 Introduction

From the end of 2019, the so-called Corona virus strain [1] have spread along the globe yielding more than 100 millions of infections and more than 3 millions of fatalities. To date this paper is written it is fully unknown if more strains are still to be expected despite of the fact that vaccine programs have been done in most countries.

As noted in [2], it was an expectant view about the arrival of a strong pandemic with similar characteristics as the AH1N1 seen in the outbreak of 2009. Certainly the ongoing situation of pandemic cannot be comparable to that scenario at the past decade [3]. Clearly the ongoing scenario has surpassed expectant models, fact that leads to establish that the corona virus is fully adaptable to various conditions [4] such as for example climate and altitude. In this manner, the virus has achieved to penetrate all geographical places in all different physiological hosts. The biochemical adaptability of virus is seen in the highest rates of infections in all continents. On the other hand one can wonder about the role of humans to extend the infections in all places. Thus one can anticipate at the human behavior and the nonlinear components. In this way emerges various questions about the factors that are favorable to the propagation of strain and the causes and the interralation among them that would be relevant to explain the fast increasing of infections per unit of time [5].

In this paper, the human behavior characterized by being one of random character and also seen as a factor of infection, is mathematically modeled through

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the main assumption that macro systems whose time evolution is dictated by the Shannon's entropy [6–8] are subjected to exhibit nonlinearities. Under this scheme it was associated the criterion of human mobility that to some extent it appears to be purely quadratic, so that it allows us to build a sustainable model that matches known statistical data of rate infections in most countries. Apart from the statistical errors, the present approach reveals us that even in the scenarios of implementation of actions that force people stay apart from each other, infections would be independent of it and it can be seen as a natural response to the human behavior that is based in mobility and randomness originated by their intrinsic behavior against other mammals and species.

The rest of paper is structured as follows: in second section the theoretical basis of this study is done. In third section the implications of model is presented having focused at the number of infections with respect to time. In fourth section the applications of model to data from Brazil, France, Mexico and Philippines is done, and finally the conclusion of paper is presented.

2 The Physics-Mathematics Machinery

Consider a finite number of local habitants defined by N and the N^ℓ the global number of people with ℓ an positive integer number. Thus one has the probability that one of them has a well-defined behavior given by:

$$\mathbf{p} = \frac{1}{N^\ell}. \tag{1}$$

Now consider that exists a finite number of habitants n^Q belonging to a social group with $Q > 0$ an integer number. Logically $n^Q \in N^\ell$. Thus, the probability that one habitant of this social group has a behavior (that for example can be matched to those of the N^ℓ is given by:

$$\mathbf{P} = \frac{1}{n^Q}. \tag{2}$$

Therefore with Eq. (1) and Eq. (2) one can built a kind of universal expression that assign a probability for each individual belonging to the

$$\mathbf{U} = \mathbf{p} \otimes \mathbf{P} = \frac{1}{n^Q N^\ell}. \tag{3}$$

Thus, it is argued that exist a Shannon's entropy [9,10] in the sense that the universal probability cannot be accurate so that instead it exhibits a well-defined uncertainty, thus the application of the Logarithm reads

$$\mathcal{H} = -\mathrm{Log}\mathbf{U} \tag{4}$$

$$= -\mathrm{Log}\left(\frac{1}{n^Q N^\ell}\right) \tag{5}$$

$$= \mathrm{Log}\left(n^Q N^\ell\right). \tag{6}$$

Thus it is feasible to postulate that exists a concrete probability of any event that affects directly the global number of habitants. As seen in Eq. (3) this probability can be a finite number of probabilities. In this way one can write down that the fraction of the affected global **H** is the outcome of single or chain or events:

$$\mathbf{H} = \left[\prod_{j}^{J} p_j\right] N^{\ell}. \quad (7)$$

In this way one can see that the product of probabilities is actually the product of events by the which affects the number N^{ℓ} due to a concrete fact that for example can be a pandemic. Under this view one can postulate that in epochs of pandemic might coexist various events that lead to establish a global pandemic. Of course, the pandemic cannot be seen as a fully negative fact, since it is proved that humans are beings capable to find the best ways to minimize the consequences of it. Then, for instance one can propose below up to three different events that might to constitute a close dynamics of pandemic:

- Mobility: Is fully inherent in all beings that carry out activities for surviving, such as bacteria that needs to carry out quorum previous to optimize any actions of chemotaxis to guarantee their motility [11,12], humans would require of mobility to accomplish their activities as well as to take decisions. Thus the action of moving can be seen as a scenario of risk permanent to be attacked by external organisms [13–15].
- Disease: The transportation of virus and bacterias to a group of humans and the subsequent infection among them is commonly done only if the rate of mobility is high enough to produce a fast infection in a global manner.[1]
- Alleviation: In a context of pandemic, once that humans have carry out quorums to conclude in the best decisions that are favorable to them and against virus spread, humans are able to implement rules that are strongly oriented to mitigate the rate of infections and therefore to expect a notorious difference between the before and after.

2.1 Probability of Mobility

Thought as the more wide and general action in humans might not to have a very specific mathematical model. Therefore, to priori we attain an inverse relationship at the sense that it is inverse to the time to the power $\ell - s$ with s a positive real number and ℓ that is the power attained to the number of habitants (see Eq. (7) N^{ℓ}). In this way we postulate the probability of human mobility as

$$p_1 = \frac{1}{t^{\ell - s}}. \quad (8)$$

The why this probability falls with time is because humans is considered a specie with limitations so in most case them are depending of artifacts to perform a

[1] Here one can mention the aerial transportation as an important vector to increase the infection in a intercontinental way.

long distance mobility, such as planes or ships, for instance. Clearly, mobility must require external resources (fuel for example) or self-efforts (pre-history civilizations that shown the nomad characteristics in the first humans). Therefore this probability should be decaying with time.

2.2 Probability of Disease

Once that humans are drawn strategies and concrete schemes to survive as well as improve their quality of life, interactions with different families of mammals or not mammals, might to pose them near to a latent risk of being randomly infected due to micro agents such as virus or bacteria. Here, it should be noted that interactions are rather related to physical variables such as space and time. It was studied in [16] where intercontinental interactions are mainly done through flights. Thus the principle of space-time propagator based on the Feynman theory was used. In fact, while humans perform social interactions, the human-human interactions would not take a large time be large, instead it in most cases these interactions are instantaneous. In this manner it is feasible to define an universal parameter a that for larger times of interaction the interaction can be broken due to stochastic fluctuations. Subsequently, one can define below the probability of infection as

$$p_2 = \frac{1}{1 + \frac{a}{t^\ell}}, \tag{9}$$

thus for scenarios by which $a \to t^\ell$ it is obvious that p_2 the probability that would determine the infection is 0.5 that exhibits not any outcome if some is infected or not (as the one when the coin is thrown). In order to illustrate it numerically, consider two people in two different interactions of 2 s and 5 s, with ℓ a variable. Below these cases have been displayed for $a = 1000$ and $a = 100$. The left-side displays the exponential behavior of probability to be infected for large times of interaction. The right-side however displays that for 2 s. The probability is of order of 0.2 yielding a small value. Aside one can note the relevant role of parameter a (Fig. 1).

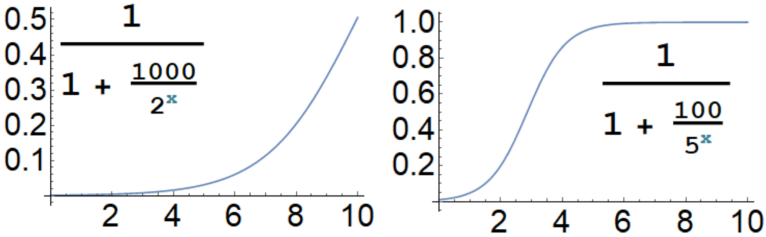

Fig. 1. Plot of Eq. (9) for the cases of $a = 1000$ (left panel) and 100 (right panel).

2.3 Probability of Mitigation

Since humans are autonomous and intelligent enough to alleviate the unexpected apparition and fast spread of strain. Only when there is common agreement in their communities or societies, unbreakable rules could be established as logic reaction to the prospective and critic scenario of an unstoppable depletion of the complete society. In this manner it is postulated that this probability would have to be favorable to humans, so that one expects the existence of a second universal parameter that would establish a high probability that guarantee the surviving of specie. On the other side, although **extinction is a remote scenario**, not any strong support is to date known that bacteria or virus have could deplete an entire specie along the first epochs of live in the planet. Based of this one can write down that the probability of mitigation can be written as:

$$p_3 = 1 - \frac{b}{t^{\ell}}, \tag{10}$$

that suggests that a high probability of mitigation is when $t^{\ell} >> b$, that would demand a large time in the sense for example: $t = 10^6$ and $\ell = 2$ then $(t = 10^6)^{\ell=2} = 10^{12}$ although b gets the value of 10^{10} then $p_3 = 1 - 10^{-2} = 0.99$ yielding a high probability of mitigation.

2.4 Formulation of Complete Probability

Having defined these three probabilities, then one can construct the complete probability of event that would affect a number of habitants N^{ℓ} due to the changes that its society might to experience due to any virus and its propagation. Then one gets that the number of affected $\mathbf{H}$ is written as:

$$\mathbf{H} = \prod_{j}^{3} p_j N^{\ell} = p_1(s,\ell)p_2(a,t,\ell)p_3(b,t,\ell)N^{\ell} \tag{11}$$

$$\mathbf{H} = \left(\frac{1}{t^{\ell-s}}\right)\left(\frac{1}{1+\frac{a}{t^{\ell}}}\right)\left(1-\frac{b}{t^{\ell}}\right)N^{\ell} \tag{12}$$

that establishes the probability that a fraction of total number of habitants defined as $\mathbf{H}$ is the net number of affected under a scenario of risk along the events of mobility, infection and alleviation (that is not a must but it is seen as an option) to keep the specie and avoid its full depletion.

2.5 Phenomenological Determination of Integer ℓ

One can wonder whether the presence of free parameters make it an instable model. As seen previously Eq. (12) was derived inside a conjecture of entropy in which the intrinsic events associated to humans would appear as consequence of the interrelation among them. The free parameter ℓ can be for example extracted from the demography in large cities. For example of this is seen for instance at

New York city with a population of approximately 10^3 around 1737 and reaching 10^6 for 1860. Another example constitutes Paris with 10^3 and 10^6 approximately at the years of 1100 and 1840 respectively. In addition, the case of country Brazil for example its population could have been of 9000 at the year of 1500 reaching 81M at year 2019. Therefore, one has that the value $\ell = 2$ can be a potential candidate to establish a realistic scenario of global infection. The incorporation of parameters is a mechanism that have been implemented in [17–20] where it was done the incorporation of models based on Machine Learning, concepts aimed to improve processes that need of a careful analysis previous to take a critic decision. With the choice of $\ell = 2$ then Eq. (12) is rewritten as

$$\mathbf{H}(t) = N^2 \left(\frac{1}{t^{2-s}} \right) \left(\frac{1}{1 + \frac{a}{t^2}} \right) \left(1 - \frac{b}{t^2} \right). \tag{13}$$

3 Implications of the Complete Probability

$\mathbf{H}(t)$ can be still rewritten in a form more understandable such as

$$\mathbf{H}(t) = N^2 t^s \left(\frac{1}{a + t^2} \right) \left(1 - \frac{b}{t^2} \right). \tag{14}$$

As defined above, the last term of product of Eq. (14) is seen as a part of an expansion in powers of the exponential function, that actually it would result in a Gaussian function. This is opportune that this exponential encloses a kind of regulation at time of the full probability $\mathbf{H}(t)$. Clearly under the assumption that $(\frac{b}{t^2})^n \approx 0$ for $n > 1$ the term $\left(1 - \frac{b}{t^2}\right)$ becomes a well-defined Gaussian function. This leads to rewrite again Eq. (14) in a compact probability:

$$\mathbf{H}(t) = \left(\frac{t^s}{a + t^2} \right) \mathrm{Exp} \left(-\frac{b}{t^2} \right) N^2. \tag{15}$$

Below in Fig. 2 two illustrations of Eq. (15) are displayed. One can see that b the parameter that drives the probability of mitigation appears to be relevant on the morphology of $\mathbf{H}(t)$ seen as the fraction of a global population N^2 that is affected by a random agent (such as the unexpected arrival of a virus such as the Corona virus 2019). Thus the mathematical structure of Eq. (15) in conjunction to curves of Fig. 2 can be interpreted as follows: the component $\left(\frac{N^2 t^s}{a+t^2}\right)$ is perceived as the risk of population that performs mobility in an environment of risk, causing a social emergence such as pandemic. On the other hand $\mathrm{Exp}\left(-\frac{b}{t^2}\right)$ denotes a kind of resilience as to a fast intervention of recovery once the virus is propagating inside the human group. In this way one goes to the position to define the rate of infections per unit of time due to a virus or aggressive micro organisms with a clear potential to damage systemic apparatus of a group of humans.

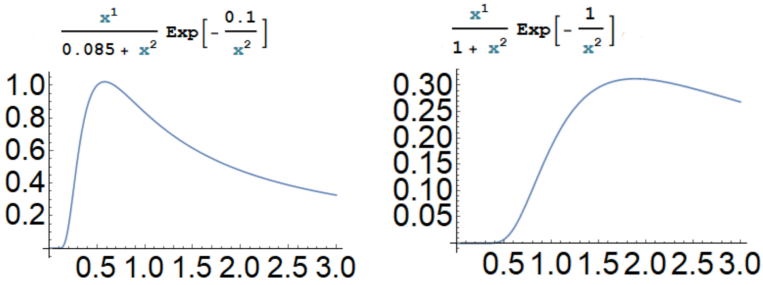

Fig. 2. Plot of Eq. (15) for the cases of a = 0.085, b = 0.1 in left panel, and a = 1, b = 1 in the right panel, here one can see the role of parameter b related to the human intervention.

3.1 Infections as Changes of Human Behavior

From the global number of habitants, then it is plausible to define the net number in risk as the derivative of $\mathbf{H}(t)$ with respect to N it is in the case that N is variable and abandons its fixed value. Then one gets:

$$\mathbf{N}(t) = \frac{d\mathbf{H}(t)}{dN} = \left(\frac{2Nt^s}{a+t^2}\right) \text{Exp}\left(-\frac{b}{t^2}\right). \tag{16}$$

Below in Fig. 3 various distributions have been displayed under the assumption that s is a variable that is attained to the mobility of humans for $b = 10$ that denotes a high intervention. It results in the flatness of all curves from a well-defined time. The flatness is an outcome of early intervention.

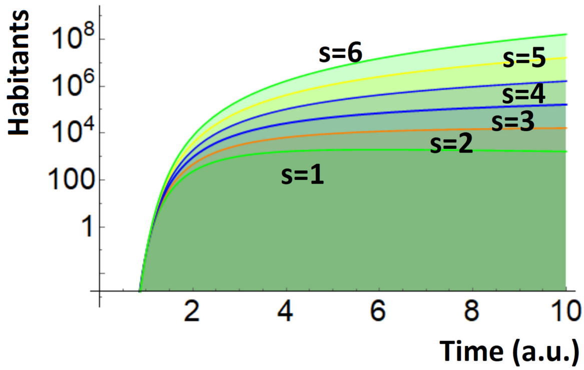

Fig. 3. A potential curve of cases by infection of virus as function of time from Eq. (16) showing the flatness of curve in certain times.

3.2 The Number of Infections

Again one can apply an additional derivative to Eq. (16) in the sense that this change would give a net number of critically affected by the presence of an external agent such as a virus causing a disease among the members of a human group. In this manner, as opted at 2020 in the beginning of ongoing Corona virus 2020 pandemic, social distancing as well as curfew actions were implemented in order to guarantee minimal human contact and therefore to expect that the curve of infections would fall down minimal values in the shortest times [21]. Thus, one expects serious changes on the infection curve in time after actions have been taken to protect people. Under this scenario, the net number of infections $\mathbf{n}(t)$ by external agent is written as:

$$\mathbf{n}(t) = \frac{d^2\mathbf{H}(t)}{dtdN} = \frac{2N}{a+t^2}\left[st^{s-1} + 2bt^{s-3} - \frac{2t^{s+1}}{a+t^2}\right]\text{Exp}\left(-\frac{b}{t^2}\right). \quad (17)$$

One can see now the apparition of up to three extra terms that are interpreted as the components that drive the morphology of $\mathbf{n}(t)$ in time and that are strongly related to the infection in particular on that terms that contain the parameter a. Thus, while attenuation is done, this does not only has a concrete effect on the mitigation of infections, it is claimed that mitigation on the social restrictions can also be seen as a disadvantageous behavior that is also implemented in the lifestyle of humans. Therefore, humans are also mitigating their selfcare due to random mobility that would exhibit a clear risk to be infected by virus. Below in Fig. 4 Eq. (17) denoting the number of infections versus time is displayed. One can see that for large values of s also large values of ℓ is needed. Thus imminently implies that N^ℓ represents the total number of a country that commonly has population at the order of various millions.

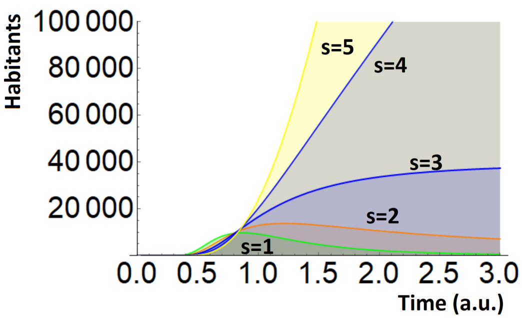

Fig. 4. Equation (17) for various values of s is displayed with s denoting the free parameter of the probability of mobility.

4 Applications and Conclusion

In Fig. 5 one can see the case of Brazil [22] whose morphology of curve of infections is to some extent similar to the case of $s = 4$. This form is seen also as a weak attenuation to create a kind of flatness of the distribution. In other words, from Eq. (17) the case of Brazil in an example where predominates the mobility and infection together as the main variables to sustain a permanent increasing number of infected people. It is supported by a small value of parameter b that poses invisible any action to mitigate the fast increasing of infections at time. Also, it is clear that from May 2020 to May 2021, the number of infections has been permanent and appears to be a line with a constant tangent.

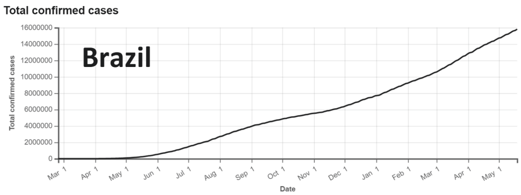

Fig. 5. Data of number of cases versus time from [22] showing the linearity as consequence of a small value of b.

In Fig. 6 the case of France is shown as sen in the data of number of infections respect to time taken from [22]. One can see that exists there up to three different periods: the first between March 2020 to August 2020 (by which is associated $s = 1$), the second one between August 2020 and December 2020 (with a potential assignation of $s = 3$), and a third one from December 2020 to February 2021 that adjusts well to the case $s = 5$. One can note that the last ones belong to scenarios that are dictated by mobility fact that makes flexible the multiple infection establishing the so-called second wave.

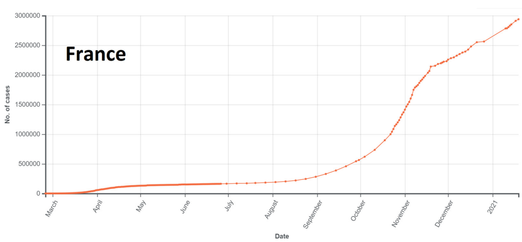

Fig. 6. The case of France fom [22] showing 3 different phases that are entirely correlated due to the evident weight of the human mobility against others variables.

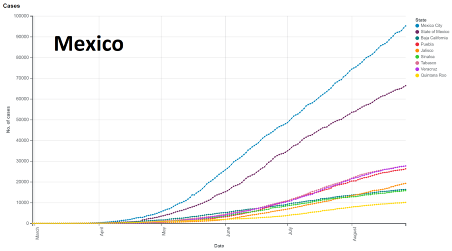

Fig. 7. The 2020 data for Mexico showing fully linear behavior for all cities that in according to Eq. (17) the present proposal indicates the high weight of mobility against other human behaviors.

In Fig. 7 the case of Mexico is shown from [22]. The data belongs to 2020 and it is given for various cities from April 2020 to September 2020, with emphasis in Mexico city that shows a fast increasing at the number of cases by the which one can adjudicate $s = 5$, denoting a little impact on the actions to mitigate the infections for instance. Again, this can also be seen as a strong magnitude of the combination of mobility and infection that is surpassing any kind of mitigation. Thus, all cities are presenting linear behaviors with minimal morphology that denotes any kind of alleviation. In Fig. 8 the case of Philippines is shown with data ranging between February 2020 to May 2021. Interestingly the data exhibits two well defined periods of infection. The first one that is dictated by $s = 1$ and a high value of b denoting a strong alleviation that produce the fall of curve in November 2020. However this alleviation appears to be weak along a **period of silent** November 2020 until February 2021. From here one can see the sharp morphology of curve that is again peaked in April 2021. One can claim that just in all those periods of silent, randomness predominates posing the system in a kind of unstable balance in the which mobility, infection and alleviation fight each other to define the identity of curve. Clearly a deep analysis of this goes beyond the scope of this paper.

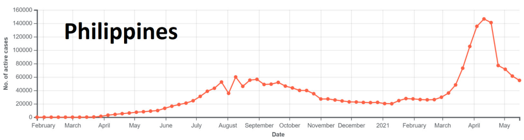

Fig. 8. The case of Philippines from [22] that exhibits two well-defined periods from the fact that the probability events might be under interference each other due to the randomness of system that does not allows to define its main identity.

4.1 Conclusion

In this paper it was investigated the contribution of the human mobility in the events of infection by virus in times of global pandemic. In this manner it was proposed a model that comes from a Shannon's entropy by the which exists a chain of probabilities that gives rise to the infection among humans. Thus the curve of infection is actually (for the view of author) the second derivative of the number of affected people by an external agent that has capabilities to deplete the specie in time. In this manner is proposed the number of infections as function of time that depends on free parameters in according to what predominates in the system: mobility, infection and alleviation. The main result of this paper Eq. (17) has been applied to the data of Brazil, France, Mexico and Philippines. It was seen that mitigation is strongly surpassed by mobility fact that sustains the infection despite of regulations such as social distance, quarantine, curfew, etc. Therefore, one can claim that human mobility is a strong factor to spread the virus in a random manner, fact that is justified by the open of terrestrial and aerial transportation at the end of first wave. Thus, people has continued to spread the virus and the different variants, fact that poses in risk the programs of vaccine. Finally the author recommends that while there is evidence of a single variant of virus, mobility would have to be blocked otherwise the apparition of more sub-types of virus can be transported among all continents making invalid the vaccines by producing again peaked distributions as seen in the case of Philippines.

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