Use of fuzzy sets, aggregation operators and multi agent systems to simulate COVID-19 transmission in a context of absence of barrier gestures and social distancing: application to an island region.

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Abstract— In this paper, we present a model of Covid-19 pandemic spreading simulated by a multi-agent system and using fuzzy sets. This paper focuses on two risk factors: age and body mass index. By using real data of people from French West Indies, we model the rate of risky population could be critical cases, if neither social distancing nor barrier gestures are respected. The results show that hospital capacities are exceeded.

Keywords—fuzzy sets, aggregation operators, multi-agent system, pandemic, island data.

I. INTRODUCTION

COVID-19 is an unprecedented pandemic by the speed and global scope of its dissemination. Most countries on the planet were not prepared to face this disease and were surprised by its spread across their territories, especially for low and middle-income countries, like most island countries for example [1]. Thus, in addition to the advice given by national and international colleges of scientists specializing in biology and medicine, simulation and forecasting tools make it possible to manage the crisis in the short, medium and long term and to curb the infection [2]. The approaches used to carry out the simulations are many and varied (see for example [57-60]). Many of these tools come from mathematical modeling, using for example, the SIR model and its extensions (see for instance [3][4][45][46]) or linear regression [5]. Some come from the fields of artificial intelligence like neural networks for instance: deep learning [6] or fuzzy neural networks [7]. And others are mixed approach using both mathematical and computer sciences tools [8]. Simulations focusing on the effect of lockdown or the effects of its absence or its reduction, are based on similar approaches: SIR model [9][10], Bayesian approaches [11] or multi-agent system [12]. In this paper, we propose to use fuzzy sets, aggregation operators and Multi-Agent System (MAS) to simulate the effect of non-compliance with barrier gestures after the removal of confinement. The interest of this approach is the combination of fuzzy sets, aggregation operators and MAS to simulate the effect of COVID-19. The simulation is made in an island context by taking the example of the archipelago of the islands of Guadeloupe, in the Caribbean. The simulation focus on the level of severity of disease (mild, severe or critical) for infected people. A special feature of this simulation is the fact that we have focused on two real risk factors which are essential to assess the severity of infected people: age and Body Mass Index (BMI). The paper is organized as follows. We present our approach in the next

section. Then, the data used for the simulation is presented. In the next section, we present the experimental results. Finally, a short discussion is made before concluding.

II. SIMULATIONS ON THE EFFECTS OF NO LOCKDOWN

A. Related works

Simulations on the effects of lockdown mainly estimate the number of deaths if there had been no lockdown or very few barrier measures [9][13]. These approaches generally have a global approach and do not take account of risk factors. For instance, the bayesian approach in [13] is global and have no particular risk factor and the SIR approach in [9] only considers age as risk factor. In [12], a MAS is proposed to simulate the effects of lockdown, by introducing age and comorbidity (cardiovascular diseases, diabetes...) as two risk factors; these risk factors are introduced in the form of probabilities. Our approach also uses risk factors and MAS, but the risk factors are introduced with fuzzy sets in order to be closer to reality.

B. General presentation of the approach

In our approach, we propose to focus on two risk factors linked to COVID-19 by introducing them as fuzzy subsets in a multi-agent system, namely age and BMI. The choice of these two risk factors is driven by the medical and statistical analysis. Older age is the main risk factor for the severe or critical case of infected people [14-17] and obesity (measured by BMI) seems to be the second main risk factor [17-20]. The main objective of the approach proposed here is to assess the grouping of infected people into the three categories (mild, severe or critical) if no barrier measure or social distancing was observed after the end of the lockdown. We are especially interested in the number of critical cases, particularly in a context where many countries do not have enough Intensive Care Units (ICU) to manage the crisis [1]. Thus, we use a MAS to modelise the population of a real archipelago, the islands of Guadeloupe, French West Indies, where the number of ICU is limited and the proportion of obesity is growing like for a lot of island regions [21][22]. The demographic (age), geographic and BMI characteristics of each agent were not chosen randomly, but according to statistical data from Guadeloupe. In addition, the use of fuzzy subsets to model age and BMI has at least two advantages:

- It allows to be more realistic at the borders between different classes. For example for BMI, if we keep classic subsets, an individual with a BMI equal to 29.9 is in the group of overweight people, while an individual with a BMI equal to 30 is in the group of obese people whereas the difference between the two is only 0.1 (for more details see [23,24])

- It makes it possible to combine the values of risk factors (age and BMI) by using fuzzy aggregation operators which reflect medical reality. For example, if an infected person is of advanced age and is obese, we know that these two elements are aggravating factors and that he will certainly develop a serious or even fatal form of COVID-19. For such values of the two factors (advanced age and obesity), a fully reinforced (or at least positively reinforced) operator will represent this aspect of aggravation of the disease.

C. The used model in MAS

For the MAS, we used and modified a model implemented in NetLogo plaform [25] called epiDEM Travel and Control [26]. epiDEM Travel and Control is based on epiDEM basic[47] (see also [48][49]), an epidemic model developed on NetLogo. The choice of the well-known NetLogo platform and an open access multi-agent epidemiological model is justified by the ease of adapting and redoing the simulation, especially for countries with low resources. The epiDEM Travel and Control model focuses on the spread of a disease on agents who can travel (or not) between different regions while observing infected, healed and possibly quarantined people. We put the emphasis on infected people by classifying them into 3 groups (mild, severe, critical) according to their age and their BMI. In our modified version, each agent represents a group of persons in the same age range according to the demographic data. We fit the parameters of the original model to allow free movement of people whether or not they are infected (no social distancing or quarantine). Details are given in the section on experimental results.

D. Fuzzyfication of age and BMI

Let's recall that a classical subset A of X is defined by a characteristic function which takes the value 0 for the elements of X not belonging to A and 1 for those which belong to A (see equation 1).

$$\chi_A : X \rightarrow \{0, 1\} \qquad (1)$$

A fuzzy subset B of X is defined by a membership function which associates to each element x of X a degree u (x) between 0 and 1, with which x belongs to B (see equation 2).

$$f_B : X \rightarrow [0, 1] \qquad (2)$$

Let us recall that we search to cluster infected people in 3 groups (or classes): mild, severe or critical. The characteristics of these groups are as follows:

- the mild group brings together people with mild symptoms and asymptomatic cases.

- the severe group brings together people with more serious conditions may possibly require hospitalization for observation but without going into intensive care.

- the critical group represents all those whose condition requires hospitalization in intensive care with possibly a vital prognosis.

In order to classify the level of the severity of COVID-19 for infected people in 3 groups, we use a fuzzyfication of the two risk factors which are age and obesity. As stated above, older age is the main risk factor for the severe or critical case and obesity is the second main risk factor. Generally, in demographic data, the population is divided into three age groups: young people, adults and the elderly. The severity of COVID-19 disease roughly corresponds to these three groups [14-17]: young people who are infected often have a mild form of the disease, adults generally have a more serious form and correspond to the group of severe patients, and elderly people represent the majority of critical cases. Obviously, this classification does not take into account other factors (illness, physical form, genetic heritage...). Thus we propose to use a fuzzyfication of the 3 groups of level of severity of the disease (in function of the age), which corresponds substantially to a classic fuzzyfication of the 3 age groups (see [44] for instance), as illustrated in Figure 1. Regarding the risk associated with obesity, work has mainly observed that this obesity has led to a form of criticism of the disease, even for people who are not old [17-20]. BMI makes it easy to characterize obesity (see Table I).

TABLE I.   NUTRITIONAL STATUS ACCORDING TO BMI
(SOURCE: WHO - WORLD HEALTH ORGANIZATION)

Nutritional status	Value of BMI (kg/m2)
Underweight	< 18.5
Normal weight	18.5 – 24.9
Overweight (Pre-obesity)	25.0 – 29.9
Obesity	≥ 30.0

However, it is more difficult to characterize mild and severe cases compared to the BMI corresponding to overweight people. Indeed, in some studies [27], overweight (also called pre-obesity) is considered to be a form of obesity and poses a risk of a critical case, while in other studies [28], the emphasis is placed on strict obesity as a critical form factor of disease. This imprecision further justifies the use of fuzzy subsets. Anyway, in the fuzzification of the BMI that we used, the values of the BMI corresponding to the overweight are placed in the group of severe forms. The fuzzification that we offer is based on the work of a medical team [23, 24] who proposed a first fuzzification of BMI (see figure 2). Our fuzzification of the 3 groups of level of severity of the disease according to BMI is presented in the figure 3.
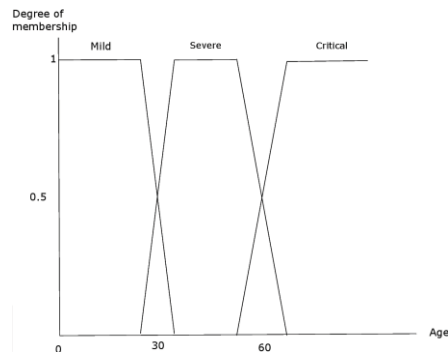

Fig. 1. Membership functions of the 3 classes in function of age (in years).

E. Aggregation operators for the evaluation of level of severity

The combination of risk factor values is a crucial step in assessing the severity of the disease. In [12], a MAS is proposed to simulate the diffusion of COVID-19, and two risk factors are introduced in the form of "death probability". In this approach, the authors systematically choose the maximum between the two death probabilities to characterize an agent. In this article, we use fuzzy aggregation operators [30][31] to combine the degrees of membership for each of the groups (mild, severe and critical). We propose an adaptive approach with several fuzzy fusion operators according to the values of the membership functions of the 3 classes (mild, severe, and critical).
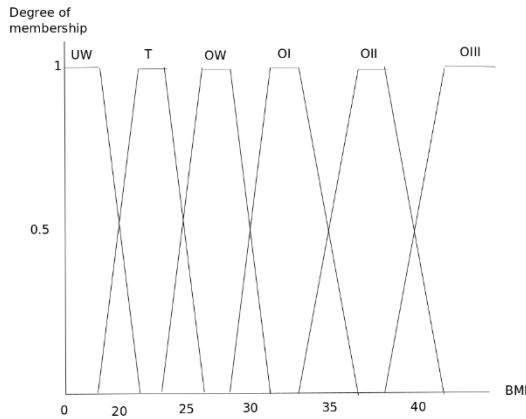

Fig. 2. Membership functions of BMI (UW=Underweight, T=Thin, OW=Overweight, OI=Obesity of grade I, OII = Obesity of grade II, OIII=Obesity of grade III also called morbid Obesity), for details, see [23][24].
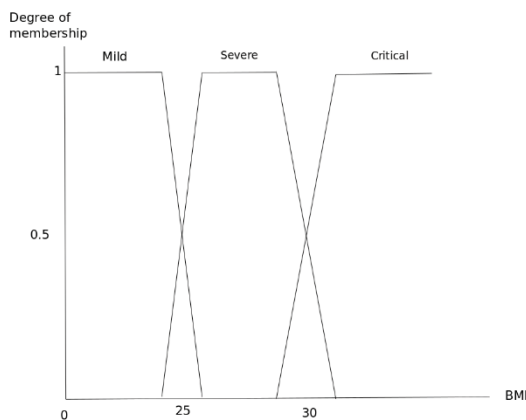

Fig. 3. Membership function of the 3 classes in function of BMI

When an agent is infected, the main task of this approach is to determine the degree of severity of the disease by computing the membership degree to each of the 3 classes and placing the agent in the class with the highest membership degree. The process is as follows.

For the two classes mild and severe, the degrees of belonging are combined with an arithmetic mean (see equation 3):

$$(f_{age}(x) + f_{BMI}(x)) / 2 \qquad (3)$$

where f_{age} is the membership degree in relation to the age and where f_{BMI} is the membership degree in relation to the BMI for the considered class.

The critical class is treated in a special way because of the risk factors and co-morbidities that strongly influence this class. With regard to the critical class, several cases are differentiated according to the value of the degrees of membership, taking 0.5 as the pivotal value. Indeed, whatever the class, if the value of the degree of membership is strictly less than 0.5, then the insertion of the agent in this class is unlikely to take place. If the value of the degree of membership is greater than 0.5 then integration into this class will be very likely to take place.

Thus, for the critical class, the considered cases are as follows:

- if the two values of the membership degrees for the critical class are strictly less than 0.5, then the data fusion is done using the arithmetic mean (see equation 3), similarly to the mild and severe classes

- if only one of the two values of membership degree for the critical class, is greater than or equal to 0.5, then the combination of the data is done using a mean type aggregation operators called OWA, Ordered Weighted Averaging [42] (see equation 4):

$$(0.3 * f_i(x) + 0.7 * f_j(x)) \qquad (4)$$

where $i, j = \{age, BMI\}$ and $f_j(x) \geq 0.5 > f_i(x)$. The value 0.7 is the weight for the membership degree greater than or equal to 0.5, and the value 0.3 is the weight for the membership degree for the membership degree is strictly less than 0.5. The choice of these weights is leaded by medical observations. Actually, for older persons, the proportion, or frequency of occurrence, or the risk of being a critical case is at least 2 times higher than for other age groups [28][50][51]. Likewise for obese people, the proportion or frequency of occurrence or the risk of being a critical case is at least twice as high as for non-obese people [52][53]. The value 0.7 being more than twice as great as 0.3, these weights represent the risks caused by old age or obesity. Thereby, the most important weight (0.7) assigned to the degree of belonging greater than or equal to 0.5 implies, for example, that biologically, a comorbidity or immunosuppression linked to age or BMI can worsen the patient's condition.

- if the degrees of membership are both greater than or equal to 0.5, then the aggregation is done using a fully reinforced operator [32], reflecting the fact that the two risk factors (age and BMI) greatly worsen the patient's condition. An operator L is fully reinforced if it is positively reinforced and negatively reinforced. An aggregation operator L whose arguments are in the interval [0, 1], has the property of positive reinforcement if when all its attributes are affirmative (i.e. greater than or equal to 0.5) it verifies:

$$L(f_1,...,f_n) \geq max (L(f_i)) \qquad (5)$$

where f_i, $i=1,...,n$ is a membership degree. Similarly, an aggregation operator L whose arguments are in the interval [0, 1], has the property of negative reinforcement if when all of its attributes are non-affirmative (i.e. less than or equal to 0.5), it verifies:

$$L(f_1,...,f_n) \leq min \ (L(f_i)) \qquad (6)$$

We propose to use the triple π operator presented in [32] which is a full reinforced operator (see equation 7):

$$\pi f_i(x) \ / \ (\ \pi f_i(x) + \pi \ (1 - f_i(x)) \ ) \qquad (7)$$

where π is the multiplication operator. The use of the triple π operator for the fusion of the two membership degree gives the following equation:

$$(f_{age}(x)* f_{BMI}(x)) / (\ (f_{age}(x)* f_{BMI}(x)) +(1-f_{age}(x))* (1-f_{BMI}(x)) \ ) \qquad (8)$$

Such a reinforced operator translates the excess morbidity caused by obesity and aging.

This adaptive approach to data fusion for belonging to the critical class enables to target in detail the patients with this level of severity of the disease. Once the aggregations have been computed, the class with the highest global membership degree is assigned to the infected patient. If several classes have the same global membership degree then the order of priority of classification is as follow: 1) class of critical cases, 2) classes of severe cases, 3) class of mild cases. This choice can be seen as a very pessimistic approach. However, some studies [54, 55] show that the estimates of the total number of cases and of the number of deaths (therefore from critical cases) are underestimated (especially because of the limited number of tests). Thus the approach that we propose can take into account cases not counted.

III. APPLICATION OF THE PROPOSED APPROACH

A. Fitting of the existing MAS epiDEM model

Before we present the results, the adaptation of the NetLogo epiDEM Travel and Control model [26] is presented for the simulation. It should be remembered that the simulation represents a situation of end of lockdown, without respect for social distancing or barrier gestures. As a result, agents can circulate freely, and infected people transmit the disease to everyone with whom it comes into contact. In the epiDEM Travel and Control model, several parameters are used to manage the isolation, hospitalization and vaccination of infected people: parameters average-isolation-tendency, average-hospital-going-tendency, initial-ambulance, inoculation-chance are all set to 0. The parameters relating to the mobility of agents are all set to 1 so as not to restrict the movements of these agents: travel-tendency, intra-mobility are set to 0 and the parameter travel (considered as boolean) is set to 1. There is also an option to create a network of random links between agents but this parameter has not been activated (for more details see [26]). Regarding the characteristics of COVID-19, the parameters are adapted to be directly linked to the disease. Average-recovery-time representing the average duration of the disease, was put around 40 days (37 days more exactly) according to medical data [14]. Infection-chance (probability of disease transmission from one individual to

another) has been set to 1, since the virus is very contagious. Finally, recovery-chance (probability of an individual's recovery under certain conditions) was set to 0.8 (see [15]).

B. Modeling and introducing the real data from Guadeloupe in the simulation

The real data used in spread simulation are coming from statistics concerning the population of Guadeloupe (FWI). For demographic information regarding age, data from the Guadeloupe archipelago in the Caribbean were recovered from data from the National Institute of Statistics and Economic Studies of France [33] and the National Observatory of Fragility [34] (data from 2015 and 2017). All of this age data is public and available on the web. For demographic information concerning BMI, the data come from a medical thesis dealing with obesity in Guadeloupe. The age and BMI data [35] were not distributed over the same age intervals, we gathered the data and organized it to harmonize according to the age groups presented in the table. The 393,000 inhabitants of the Guadeloupe archipelago were modeled by 3,924 agents. Each agent represents a group of around 100 people. These agents were distributed in 4 zones representing the different islands of the archipelago: 3 rectangular zones for the smallest islands (Les Saintes, Marie-Galante, Désirade) and the rest for Guadeloupe (composed of two very close islands). The distribution was made respecting the demography of each island, according to age. More specifically, an agent represents a group of 100 people of the same age range.

The age ranges used for the population distribution that we used to harmonize the age and BMI data are as follows: [0 - 24 years], [25 -54 years], [55 - 64 years], [65 years and over] (see example of demographic data in table II).

TABLE II. EXAMPLES OF DEMOGRAPHIC DISTRIBUTION (NUMBER OF INHABITANTS) BY AGE RANGE FOR TWO ISLANDS IN THE ARCHIPELAGO.

Age range in years	Island of Désirade	Island of Marie-Galante
[0 – 24]	374	2 876
[25 – 54]	562	3694
[55 – 64]	220	1605
[65 and over]	289	2576

For all the islands of the archipelago, the distribution of the BMI by age group is given in table III.

TABLE III. PERCENTAGE DISTRIBUTION OF DIFFERENT NUTRITIONAL STATUS (FROM BMI) ACCORDING TO AGE RANGES.

Age range in years	Underweight	Normal weight	Overweight	Obesity
[0 – 24]	not available			
[25 – 54]	2,43	48,56	36,73	12,26
[55 – 64]	3,6	33,9	46,4	16,1
[65 and over]	4,2	44,4	31,9	19,5

The distribution of nutritional status of the agents of each island is computed according to percentage of the table III. Note that data for the 0-24 year interval was not available. To simulate the conditions for the end of confinement on the Guadeloupe archipelago, we have introduced the number of suspected cases rather than confirmed cases on these islands. Indeed, the number of tests available on this territory being

very limited, the 155 confirmed cases did not seem to correspond to reality. The feedback from the town doctors [37][38] and the mathematical models [39][40] allow us to estimate the number of suspected real cases around 2000. We therefore introduced 20 infected agents into the simulation and we evaluated the number of sick agents after 30 days.

C. Implementation

The program was written and executed on the Netlogo platform. The number of runs for a simulation often varies, depending on the discipline and experience. For example, in two simulations [12][41] based on MAS, the number of simulations is completely different: in [41] , Carbo et al. performed a simulation using NetLogo (which is not linked to COVID-19) and did 30 runs of simulation; in [12] Bouchnita and Jebrane [12] proposed a simulation modeling the COVID-19 and did 3 runs of simulation. We have tested 1000 runs of the simulation of 30 days (without parallelism) on a computer cluster with 35 nodes (32 Intel dual-processor "compute" nodes, 12 or 16 cores per node, 64 GB or 128 GB of RAM per node, and 3 "graphics" nodes of the same type as the compute nodes but with an NVidia graphics). The purpose of this large number of simulation runs is to avoid falling into a local minimum. The CPU time for the 1000 numerical simulations of the disease transmission in 30 days is around 4.5 hours on the computer cluster.

D. Experimental results

We present here the numerical results for the 1000 runs of the simulation of transmission of COVID-19 in 30 days, in the Guadeloupe islands, after then end of the lockdown, without social distancing, nor barrier gesture, with an initial number of 20 infected agents for a total population of 3,924 agents. The first results we present are the average values (from 1000 experiments) of the number of people infected and the different levels of severity of COVID-19. In Table IV, we can see that without barrier measures and social distancing, the number of people infected would be around 15,900 people (159 agents), or around 4% of the total population of Guadeloupe. But it is especially the number of critical cases which is alarming since 4000 people would be in a critical state requiring care in the intensive care unit while Guadeloupe currently has only about sixty resuscitation units.

TABLE IV.   MEAN NUMBER OF INFECTED PEOPLE ON THE 1000 RUNS OF SIMULATION.

Levels of severity	Mean number of infected agents
Mild	40.457
Severe	57.323
Critical	61.869
Total	159.649

We also compute the mean and the standard deviation of each level of severity for the two risk factors, age and BMI. The results are given in table V and provide interesting results.

TABLE V.   MEAN AND STANDARD DEVIATION OF EACH LEVEL OF SEVERITY FOR THE TWO FACTOR RISKS, AGE AND BMI.

Levels of severity	Age (in years)		BMI	
	Mean	Standard deviation	Mean	Standard deviation
Mild	17.73	15.3	15.03	7.87
Severe	47.27	19.97	24.28	3.66
Critical	66.39	24.20	30.17	7.58

For instance, the mean age for the critical cases is 66.39 years, with a standard deviation of 24.20 that means a person of 40 years old can be in critical case because of he is obese.

We also estimated the link between the number of critical cases and the total number of patients, using a simple linear regression. In the figure 4, we see that the model is linear and that it is robust since it does not depend on the number of experiments.
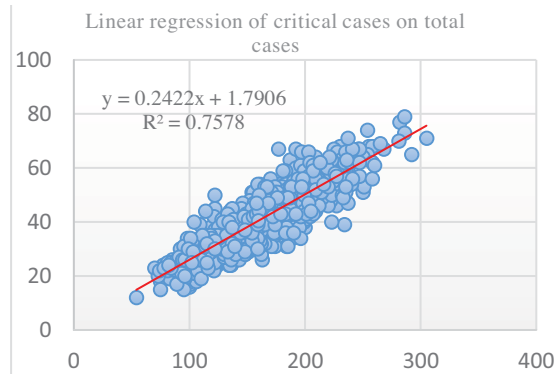

Fig. 4.   Linear regression (in red) of critical cases on total cases (for the 1000 runs). The abscissa axis represents the total number of cases and the ordinate axis represents the number of critical cases.

The value of the slope coefficient of the straight line (0.2422) indicates that in the simulation the number of critical cases represents about a quarter of the total number of infected people. This proportion is close to certain real data [14]. In addition, if we look at the proportion of age groups at the level of the critical cases presented in the table VI, we see that the vast majority of these critical cases are elderly (which is coherent with the results of table V). However, it should be noted that more than 30% of these critical cases are people in the adult age group (25-55 years). Again, although this proportion of adults among critical cases seems high, it is very similar to some medical data [28] observed in reality.

TABLE VI.   MEAN NUMBER AND PERCENTAGE OF CRITICAL CASES BY AGE GROUP (FOR 1000 RUNS OF THE SIMULATION)

Age group	Critical cases	
	Mean number of infected agents	Percentage
youth	0,228	0,57
adults	14,869	36,75
the elderly	25,36	62,68

We also carried out another series of 1000 runs of the simulation by changing the initial number of infected people with a more pessimistic view since for these 1000 other runs, the initial number of patients was 50,000, that is to say 500 infected agents in the system. Again we performed a linear regression (see Figure 5) and the value of the slope coefficient of the line was 0.3487, which is quite close to the value found for the slope coefficient with 20 infected agents. Thus, the proportion of the number of critical cases in relation to the total number of infected cases does not seem to depend on the initial number of patients: the method seems to be stable and gives no chaotic values.
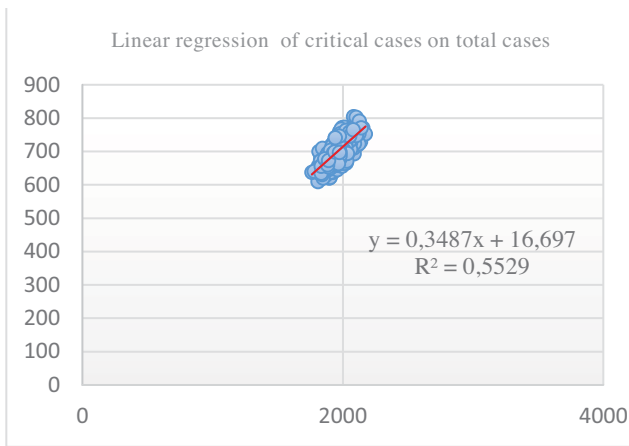
Fig. 5. Linear regression (in red) of critical cases on total cases (for the new 1000 runs) for 500 infected agents initially. The abscissa axis represents the total number of cases and the ordinate axis represents the number of critical cases.

IV. Discussion

We have presented the first results for a simulation of COVID-19 spread in island context and without social distancing, nor barrier gesture. The results show that 15,900 people (159 agents), or around 4% of the total population of Guadeloupe can be infected, and especially the number of critical cases can be alarming since 4000 people would be in a critical state requiring care in the intensive care units. One could say that this approach is exaggerated, very pessimistic and unrealistic. However the statistics of the pandemic on this archipelago during the last weeks, show that this simulation is more and more close to reality. Indeed, the experimental results of our approach were carried out in July; and since the end of August, the number of infected people has exceeded 1,000 cases per week, as shown in Figure 6. As of this writing, the number of cases is over 5,000. Restrictive measures have been taken by local and national authorities but if these are not respected, the average of the total number of cases in our simulation (15,900) could be reached within a few weeks. The approach proposed in this paper therefore seems to be relevant.
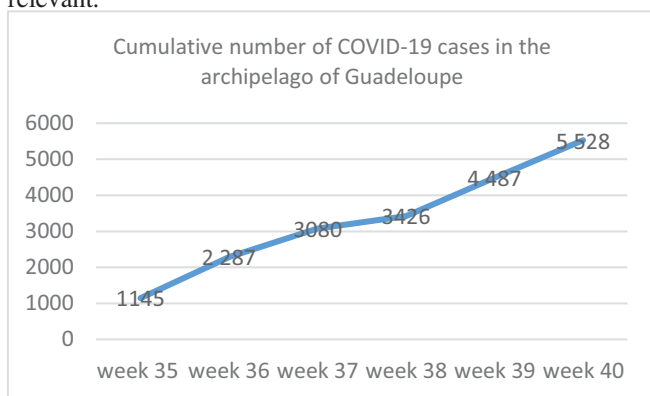

Fig. 6. Cumulative number of COVID-19 cases in the archipelago of Guadeloupe from week 35, at the end of August 2020, to week 40 at the end of September 2020 (data source: see [56]).

We focus on two risk factors, age and BMI, but other parameters could have been taken into account. For example, in France there is a fragility factor which takes into account

the health and socio-economic aspects of individuals. This factor was not taken into account in this simulation and it could have refined the simulation. Furthermore, to merge the information, we used a simple arithmetic mean as well as an OWA, and a fully reinforced operator, the triple Pi. Other operators could have been used, such as the mean triple Pi [43] instead of the arithmetic mean. All these elements can vary the results of the simulation but the main objective of this simulation was to show the consequences of the end of confinement without respecting barrier gestures. For an archipelago like Guadeloupe, the consequences could have been dramatic, with a number of critical cases requiring a UCI far greater than the number of beds and which would have caused the local hospital system to explode. The simulation therefore confirms that it is necessary to respect social distancing and barrier gestures. The second waves or worrying clusters in certain regions of the world come to co-support these results.

V. Conclusion

In this paper, we have presented an approach allowing to model and simulate the diffusion of COVID-19 in an insular context, considering a non-respect of social distancing and barrier gestures. The interest of this approach is the combination of fuzzy sets, aggregation operators and MAS to simulate the effect of COVID-19. The simulation focus on the level of severity of disease (mild, severe or critical) for infected people and two real risk factors (Age and Body Mass Index) which are essential to assess the severity of infected people. Another originality of this simulation is of using real data. Data from the Guadeloupe archipelago have been used and the results show that non-compliance with barrier gestures and social distancing could lead to a very large number of patients, in particular people in critical condition, beyond of the capacities in intensive care beds for island regions. The interesting result is the prediction of this modelling. Without confinement one quart of risky population could have been in medical reanimation. Of course, this model focuses only on two parameters to characterize risky population, but for the moment they are the most representative for epidemiologists in the case of Covid-19. Among the perspectives envisaged, the use of other risk factors, based on social conditions and autoimmune diseases represented on the form of fuzzy sets are considered to be introduced in the model.

References

[1] X. Ma and D. Vervoort, "Critical care capacity during the COVID-19 pandemic: Global availability of intensive care beds," Journal of Critical Care, vol. 58, pp. 96–97, August 2020.

[2] C.S.M. Currie et al, "How simulation modelling can help reduce the impact of COVID-19," Journal of Simulation, pp. 1747–7786, 2020.

[3] J.T. Wu et al., "Estimating clinical severity of COVID-19 from the transmission dynamics in Wuhan, China," Nature Medicine, vol. 26, pp. 506–510, April 2020.

[4] W. C. Roda, M. B. Varughese, D. Han and M. Y. Li., "Why is it difficult to accurately predict the COVID-19 epidemic?" Infectious Disease Modelling, vol. 5, pp. 271–281, 2020.

[5] J. F. Rustam et al., "COVID-19 Future Forecasting Using Supervised Machine Learning Models," IEEE Access, vol. 8, pp. 101489–101499, 2020.

[6] V. K. R. Chimmula and L. Zhang, "Time series forecasting of COVID-19 transmission in Canada using LSTM network," Chaos, Solitons and Fractals , vol. 135, 2020.

[7] M. A. A. Al-qaness, A. A. Ewees, H. Fan, L. Abualigah and M. A. Elaziz, "Marine Predators Algorithm for Forecasting Confirmed Cases of COVID-19 in Italy, USA, Iran and Korea," Int. J. Environ. Res. Public Health, vol. 17, 2020.

[8] S. J. Fong, G. Li, N. Dey R.G. Crespo and E. Herrera-Viedma, "Composite Monte Carlo decision making under high uncertainty of novel coronavirus epidemic using hybridized deep learning and fuzzy rule induction," Applied Soft Computing Journal, vol. 93, 2020.

[9] J. Roux, C. Massonnaud and P. Crépey, "TCOVID-19: One-month impact of the French lockdown on the epidemic burden," unpublished, medRxiv preprint, https://doi.org/10.1101/2020.04.22.20075705, April 2020.

[10] M. Ali, S. T. H. Shah, M. Lmran and A. Khan, "The role of asymptomatic class, quarantine and isolation in the transmission of COVID-19, Journal of Biological Dynamics," Journal of Biological Dynamics, vol. 14, 2020.

[11] P. Nouvellet, S Bhatia, A Cori et al., "Reduction in mobility and COVID-19 transmission," Imperial College London, https://doi.org/10.25561/79643, June 2020.

[12] A. Bouchnita and A. Jebrane, "A hybrid multi-scale model of COVID-19 transmission dynamics to assess the potential of non-pharmaceutical interventions," Chaos, Solitons and Fractals, vol. 138, 2020.

[13] S. Flaxman, S. Mishra, A. Gandy et al., " Estimating the number of infections and the impact of non-pharmaceutical interventions on COVID-19 in 11 European countries.," Imperial College London, https://doi.org/10.25561/77731, March 2020.

[14] F. Zhou et al., "Clinical course and risk factors for mortality of adult inpatients with COVID-19 in Wuhan, China: a retrospective cohort study," The Lancet, vol. 395, pp. 1054–1062 ,2020.

[15] Z. Wu and J. M. McGoogan, "Characteristics of and Important Lessons From the Coronavirus Disease 2019 (COVID-19) Outbreak in China," JAMA, vol. 323, pp. 1239–1242 ,April 2020.

[16] E. Williamson et al., " OpenSAFELY: factors associated with COVID-19-related hospital death in the linked electronic health records of 17 million adult NHS patients," medRxiv preprint, https://doi.org/10.1101/2020.05.06.20092999, May 2020.

[17] Haut Conseil de la santé publique (France), "Opinion on the prevention and management of patients at risk for serious forms of COVID-19 as well as the prioritization of diagnostic tests (Avis relatif à la prévention et à la prise en charge des patients à risque de formes graves de COVID-19 ainsi qu'à la priorisation des tests diagnostiques)",https://dwww.hcsp.fr, March 2020.

[18] G. Muscogiuri, G. Pugliese, L. Barrea, S. Savastano and A. Colao, "Obesity: The "Achilles heel" for COVID-19?," Metabolism Clinical and Experimental, vol. 108, 2020.

[19] D. A. Kass, P. Duggal and O. Cingolani, "Obesity could shift severe COVID-19 disease to younger ages," The Lancet, vol. 395, pp. 1544, May 2020.

[20] J. Lighter et al., "Obesity in patients younger than 60 years is a risk factor for Covid-19 hospital admission," Oxford University Press PHEC, April 2020.

[21] FAO Regional Office for Latin America and the Caribbean, "United Nations calls for urgent action to curb the rise in hunger and obesity in Latin America and the Caribbean," http://www.fao.org/americas/noticias/ver/en/c/1250656/, 2019.

[22] A. K. McLennan and S. J. Ulijaszek, "Obesity emergence in the Pacific islands: why understanding colonial history and social change is important," Public Health Nutrition, vol. 18, pp. 1499–1505, May 2020.

[23] S. A. Miyahira and E. Araujo, "Fuzzy Obesity Index for obesity treatment and surgical indication," 2008 IEEE International Conference on Fuzzy Systems, 1-6 June 2008, Hong Kong, China.

[24] S. A. Miyahira, J. L. Moreira Coutinho de Azevedo and E. Araujo, "Fuzzy obesity index (MAFOI) for obesity evaluation and bariatric surgery indication," Journal of Translational Medicine vol. 9, 2011.

[25] U. Wilensky, "NetLogo," Center for Connected Learning and Computer-Based Modeling, Northwestern University, Evanston, IL, http://ccl.northwestern.edu/netlogo/, 1999.

[26] C. Yang and U. Wilensky, "NetLogo epiDEM Travel and Control model," Center for Connected Learning and Computer-Based Modeling, Northwestern University, Evanston, IL, http://ccl.northwestern.edu/netlogo/models/epiDEMTravelandControl , 2011.

[27] F. Gao, K.I. Zheng, X.B. Wang, et al., "Obesity is a risk factor for greater COVID-19 severity," Diabetes Care, 2020

[28] C.M. Petrilli, S.A. Jones, J. Yang, et al., "Factors associated with hospitalisation and critical illness among 5279 patients with coronavirus disease 2019 in New York city prospective cohort study," BMJ, vol. 369, 2020

[29] I. Bloch and A. Hunter (Eds), "Fusion : General concepts and characteristics," Journal of Intelligent Systems, vol. 16, pp. 1107–1134, 2001

[30] I. Bloch and A. Hunter (Eds), "Fusion : General concepts and characteristics," International Journal of Intelligent Systems, vol. 16, pp. 1107–1134, 2001

[31] D. Dubois and H. Prade, "On the use of aggregation operations in information fusion process," Fuzzy Sets and Systems, vol. 142, pp. 143–161, 2004.

[32] R. Yager and A. Rybalov, "Full reinforcement operators in aggregation techniques," IEEE Transactions on Systems, Man, Cybernetics-Part B : Cybernetics, vol. 6, 1998.

[33] INSEE (France) National Institute of Statistics and Economic Studies of France, "Complete file of the department of Guadeloupe (Dossier complet du département de la Guadeloupe)," https://www.insee.fr/fr/statistiques/2011101?geo=DEP-971, 2015.

[34] Observatoire National des fragilités (France) National Observatory of Fragility of France, "Guadeloupe Regional Fragility Observatory (Observatoire régional des fragilités de Guadeloupe) ,"https://www.observatoires-fragilites-grand-sud.fr, 2020.

[35] P. Carrere, "Arterial hypertension, obesity, precariousness in Guadeloupe, the CONSTANT survey (HTA, obésité, précarité en Guadeloupe, l'enquête CONSANT),," MD,http://www.hta-gwad.com/admin/publis/these_carrere_consant_ultime.pdf ,2010

[36] R. Yager and A. Rybalov, "Full reinforcement operators in aggregation techniques," IEEE Transactions on Systems, Man, Cybernetics-Part B : Cybernetics, vol. 6, 1998.

[37] M. Amor, "Covid-19: a new quantified approach is a game-changer (Covid-19 : une nouvelle approche chiffrée change la donne)," Frances Antilles News Papers, https://www.guadeloupe.franceantilles.fr/actualite/sante/coronavirus/covid-19-une-nouvelle-approche-chiffree-change-la-donne-568553.php, April 2020.

[38] Guadeloupe 1ière TV "Coronavirus: Much larger real numbers here (Coronavirus : Des chiffres réels beaucoup plus importants chez nous)," https://la1ere.francetvinfo.fr/guadeloupe/coronavirus-des-chiffres-reels-beaucoup-plus-importants-chez-nous-821842.html, April 2020.

[39] H. Salje et al., "Estimating the burden of SARS-CoV-2 in France," Science, May 2020.

[40] L. Roques, E. K. Klein, J. Papaïx, A. Sara and S. Soubeyrand, "Using Early Data to Estimate the Actual Infection Fatality Ratio from COVID-19 in France", Biology, vol. 9, May 2020.

[41] J. Carbo, N. Sanchez-Pi and J. M. Molina, "Agent-based simulation with NetLogo to evaluate ambient intelligence scenarios," Journal of Simulation, vol. 12, pp. 42–52, 2018.

[42] R. Yager, "On ordered weighted averaging operators in multi-criteria decision making," IEEE Trans. Systems, Man, and Cybernetics, vol. 18, pp. 183–190, Jan/Feb 1988.

[43] R. Emilion, S. Régis and A Doncescu, "A general version of the triple Π operator," International Journal of Intelligent Systems, vol. 28, pp. 957-973, 2013

[44] M. Escabí, "Chapter 11 - Biosignal Processing", in Introduction to Biomedical Engineering (Third Edition), Biomedical Engineering, J. Enderle, J. Bronzino (Eds), Pages 667-746, 2012

[45] G. Giordano et al, "Modelling the COVID-19 epidemic and implementation of population-wide interventions in Italy", Nature Medicine, vol 26, pp. 855–860, June 2020

[46] B. Ivorra, M.R. Ferrández, M. Vela-Pérez, A.M. Ramos, "Mathematical modeling of the spread of the coronavirus disease 2019 (COVID-19) taking into account the undetected infections. The case of China", Commun Nonlinear Sci Numer Simulat. vol. 88, 2020

[47] C. Yang and U. Wilensky, "NetLogo epiDEM basic," Center for Connected Learning and Computer-Based Modeling, Northwestern University, Evanston, IL, http://ccl.northwestern.edu/netlogo/models/epiDEMTravelandControl , 2011.

[48] Z. Wang, H. Zhao, Z. Lai, and X. Qin, "Improved SIR epiDEM model of social network marketing effectiveness and experimental simulation", Xitong Gongcheng Lilun yu Shijian/System Engineering Theory and Practice, vol. 36, pp. 2024-2034, 2016

[49] M.C. Smith and D.A Broniatowski. "Modeling Influenza by Modulating Flu Awareness". In: Xu K., Reitter D., Lee D., Osgood N. (eds) Social, Cultural, and Behavioral Modeling. SBP-BRiMS 2016. Lecture Notes in Computer Science, vol. 9708, 2016

[50] R. Verity et al., "Estimates of the severity of coronavirus disease 2019: a model-based analysis", The Lancet Infectious Diseases, vol. 20, June 2020

[51] A. Banerjee et al. "Estimating excess 1-year mortality associated with the COVID-19 pandemic according to underlying conditions and age: a population-based cohort study", The Lancet, vol. 395, May 2020

[52] Q. Cai et al., "Obesity and COVID-19 Severity in a Designated Hospital in Shenzhen, China", Diabetes Care, vol. 43, pp 1392–1398, 2020

[53] C. Caussy et al., "Prevalence of obesity among adult inpatients with COVID-19 in France", The Lancet Diabetes & Endocrinology, vol. 8, pp 562–564, July 2020

[54] K. M. Jagodnik, F. Ray, F. M. Giorgi, and A. Lachmann, "Correcting under-reported COVID-19 case numbers: estimating the true scale of the pandemic", unpublished, medRxiv preprint, doi: https://doi.org/10.1101/2020.03.14.20036178, April 2020

[55] J. Shuja, E. Alanazi, W. Alasmary and A. Alashaikh, COVID-19 open source data sets: a comprehensive survey, Applied Intelligence, 2020

[56] Agence régional de Santé de Guadeloupe, "Regional Health Agency of Guadeloupe. Guadeloupe weekly situation update (Point de situation hebdomadaire Guadeloupe)", https://www.guadeloupe.ars.sante.fr/coronavirus-informations-et-recommandations-0, October 2020

[57] K. Prem et al, "The effect of control strategies to reduce social mixing on outcomes of the COVID-19 epidemic in Wuhan, China: a modelling study", The Lancet Public Health, vol. 5, pp 261-270, May 2020

[58] C.Anastassopoulou, L. Russo, A. Tsakris and C. Siettos, "Data-based analysis, modelling and forecasting of the COVID-19 outbreak", PLoS ONE, vol. 15, March 2020

[59] S. Hsiang et al, "The effect of large-scale anti-contagion policies on the COVID-19 pandemic", Nature, vol. 584, pp 262–267, 2020

[60] S. Zhao and H. Chen, "Modeling the epidemic dynamics and controlof COVID-19 outbreak in China", Quantitative Biology, vol. 8, pp 11–19, 2020