A MARKOV CHAIN MODEL FOR COVID19 IN MEXICO CITY

A PREPRINT

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ABSTRACT

This paper presents a model for COVID19 in Mexico City. The data analyzed were considered from the appearance of the first case in Mexico until July 2021. In this first approximation the states considered were Susceptible, Infected, Hospitalized, Intensive Care Unit, Intubated, and Dead. As a consequence of the lack of coronavirus testing, the number of infected and dead people is underestimated, although the results obtained give a good approximation to the evolution of the pandemic in Mexico City. The model is based on a discrete-time Markov chain considering data provided by the Mexican government, the main objective is to estimate the transient probabilities from one state to another for the Mexico City case.

Keywords Probability · Stochastic Processes · Markov Chain · COVID19

1 Introduction

Coronavirus is a disease caused by several viruses, those who gets this disease are likely to develop respiratory infections or complications that can even lead to death. However, there are people infected by the virus who do not show any symptoms, that is, they are carriers of the virus and do not show some of the following symptoms: fever, headache, runny nose, respiratory problems, dry cough, even loss of smell and taste.

According to Chinese health authorities, the first time it was detected in the seafood market of the city of Wuhan, on November 17, 2019. At the end of December, the Chinese government informed the World Health Organization about these new cases of unknown origin. On January 1, 2020, the World Health Organization (WHO) asked the local authorities for more information on these detected cases to establish the level of risk of both contagion and spread of this new disease. On January 3, after 55 cases of atypical pneumonia were reported, the Chinese government identified this new family of viruses, Coronavirus, as the cause of this new and dangerous disease. Finally, on February 11, the WHO formally named the disease COVID-19. On March 11, 2020, the WHO because of the spread of the virus in several countries, concluded that COVID-19 should be considered a pandemic, and expressed concern about the existence of a significant number of cases in such a short time in most parts of the world, and urged governments to implement response measures to this emerging health emergency. More information about the pandemic spread can be found in Gilmour et al., Giordano et al., He et al., Roda et al..

COVID-19 is a respiratory-type virus that is transferred from person to person either by contact with drops of saliva from an infected person, which can be expelled when coughing or sneezing and even when talking. The general symptoms are fever, fatigue, respiratory problems, dry cough, even loss of smell and taste, with eventual diarrhea. Some patients have mild symptoms, but some more have serious health problems and may even lose their lives.

The main recommended health contingency measures were the following: keep at least one meter of distance between people, use masks when having relationships with people in any type of situation; avoid closed, congested spaces or in which it is impossible to keep a distance of at least one meter away, keep windows and doors open to promote ventilation in closed spaces. The sanitary measures to prevent the spread of the virus that causes COVID19 disease are:

wash your hands regularly and carefully with soap and water; in the absence of soap and water use hydro alcoholic gel, avoid touching the eyes, nose, and mouth with dirty hands, when coughing or sneezing, cover the mouth and nose with the elbow flexed or with a handkerchief, as well as cleaning and disinfecting frequently surfaces, particularly those that are touched regularly. After a year of pandemic, it is known that the population sector most affected or more likely to lose their lives as a result of having been infected by the virus, is that people of advanced age or with comorbidities such diabetes, hypertension, obesity, diseases lung problems, kidney problems, immunity problems, asthma, or heart problems. On February 28, 2020, jointly, the Pan American Health Organization and the WHO, through the document epidemiological updates, indicated the existence of the first confirmed cases of COVID19. Both cases coincided with the antecedent of having made a trip to Italy before the presentation of symptoms of the disease. After that the government of Mexico City made known to its population the means through which a person infected by the SARS-CoV-2 virus could infect others, mainly through drops of saliva that expelled a person infected by coughing or sneezing, or by contact with a surface contaminated by the virus and subsequently putting contaminated hands to the face, touching the mouth, nose or eyes.

Unfortunately, Mexico is one of the countries most affected by the spread of the disease, at the moment this is written, it ranks fourth in the number of deaths. As part of the response to the health emergency caused by this new SARS-CoV-2 virus, scientists, academics, and experts from different areas have been collaborating and designing strategies to combat the COVID19 pandemic. Specifically, the National Council of Science and Technology works together with the government of Mexico, who, under the coordination of the Ministry of Health, began collaboration in various projects: design of data science tools that make data available to the population data and information in real-time.

2 The epidemic SIR model

Scientists use mathematical models to predict the progression of diseases and understand how the interventions of the authorities affect the spread of the disease. More complex models serve to help in decision-making and make more efficient use of resources as well as the consequences of health contingency measures implemented by health authorities. One of the simplest, to estimate the spread of the disease divides the population that is susceptible to infection into three categories according to their stage concerning the disease. Those who have not yet become ill but who can contract it are called susceptible. Those people who have already been infected go from being susceptible to being infected. The third group is of recovered people, that is, those who after suffering the disease have recovered and become immune or unfortunately have died, these people can no longer be infected or spread the disease, this model is known as the SIR model Donsimoni et al., Gilbert et al., Hamzah et al., Tuckwell and Williams. This model can provide an estimate of the total number of infections with and without the intervention of the health authorities. One of the parameters of interest to estimate is the reproduction number, the average number of infections that an infected person can cause in a given time, it is known that if this reproduction number takes values lower than the unity, then the disease will disappear Su et al., Wan et al.. The proportion of infected people who die as a result of the disease is called the fatality rate. The COVID19 case fatality rate depends significantly on the age and presence of comorbidities of people with the disease.

Among the health contingency measures, the most important are quarantine and isolation, which contribute to reducing the speed of transmission, and therefore the number of reproduction. Isolating infected people reduces the rate of spread while quarantining healthy people reduces the susceptible population and therefore the virus is less likely to spread and prevail among the population Arenas et al.. One of the most effective measures to control and eradicate the disease is vaccination, with the application of vaccines, people move from the susceptible sector to the removed sector without becoming infected, reducing the size of the susceptible population, so the disease will finally be controlled.

Description of the SIR model

The SIR model describes the behavior of the disease, this model was developed by Kermack Kermack and McKendrick, this model assumes that each of the members of the population belongs to one of the following three states: Susceptible, Infected and Recovered. Those who are susceptible are those who do not yet have the disease, but who are not immune to it, therefore they can be infected if they have contact with someone who is sick. Infected people are those people who currently have the disease and can transmit it to other people. Recovered people are those who have already suffered from the disease and who can no longer transmit it to other people, nor can they be reinfected.

This model can incorporate more specifications regarding the spread of the virus, however, in most cases, they are a simplification and approximation of reality. Its level of precision will depend on the assumptions made and how much they reflect reality. Some assumptions do not necessarily apply to reality, such as that each individual has the same probability of coming into contact with any other member of the population, that is, it does not consider the fact that contacts are more likely between people geographically and socially closer. Another assumption is that there are people more susceptible to being infected than others, in addition, there are people who have a greater number of contacts than

others, also it is assumed is that once a person has been infected, the recovery time depends on the time that has elapsed since the infection, among others.

Recent work about SIR model with applications and generalizations can be found in [Ball et al., 2019, Carcione et al., 2020, Chen et al., 2020, Cortés et al., 2020, Huppert and Katriel, 2013, Mahmud and Lim, 2020], also [Bernhardt, 2020, Diekmann et al., 2012, Fraser et al., 2004, Hethcote, 2000, Yanchevskaya and Mesnyankina, 2019].

3 Fundamentals

General stochastic processes are widely used in epidemic analysis, bayesian models also have been used in the study of COVID19, for example [Allen, 2017, Arumugam and Rajathi, 2020, Bertozzi et al., 2020, Britton, 2010, Catak and Duran, 2020, Kharroubi, 2020, Mbuvha and Marwala, 2020, Silva et al., 2020, Şenel et al., 2020, Zhang and Du, 2020].

Markov Chains preliminars

Markov chains have proven to be useful tools for modeling important problems that appear in medicine, in particular, they have been successfully applied to model the dynamics of epidemics, that is, the rapid spread (transmission) of an infectious disease to large numbers of individuals in a given population. Factors whose nature is uncertain and whose current state depends on the previous levels of the disease, the application of probabilistic models, such as Markov chains, is a natural and powerful approach.

A Markov Chain is a sequence of events for which the probabilities of outcomes or states depend on what happened previously. The data are obtained in time intervals (for instance hours, days, weeks, years) that is, there is a succession of values of a certain variable that are successively obtained in time.

A stochastic process is defined as a collection of random variables, $\{X_t, t \in T\}$, T index set, ordered by the subíndex t which usually denotes time. The possible value that the random variable can take is called a state space, S, so this state space can be discrete or continuous. A discrete-time Markov chain is a stochastic process with a discrete state space, S, such that for

 $\{X_0 = x_0, X_1 = x_1, \dots, X_n = x_n\}$, the property (1) is satisfied

$$P(X_{n+1} = x_{n+1} | X_{n-1} = x_{n-1}, \dots, X_0 = x_0) = P(X_{n+1} = x_n | X_n = x_n).$$
(1)

A Markov chain is said to be homogeneous if for any value of $n \ge 0$ and any elements of the state space $i, j \in S$ holds that $P(X_{n+1} = j | X_n = i) = P(X_1 = j | X_0 = i)$. This probabilities are denoted by p_{ij} and is called the transition matrix $P = (p_{ij})$ for $i, j \in S$.

If for each element of the state space S we have that $P(X_0 = i) = \mu_i$, $i \in S$, where $\mu = (\mu_i)_{i \in S}$ meets the condition $\sum_{i \in S} \mu_i = 1$, μ is called the initial distribution. The inputs of the P matrix verify that $\sum_{j \in S} p_{ij} = 1$ is for all $i \in S$, so it is called a stochastic matrix. Also, a Markov chain is determined by its state space, its initial distribution, and its transition matrix, the stochastic matrix.

As regards the SIR model, this model assumes that time is discrete, the variable t takes values in $\{0, 1, 2, \ldots, \}$, therefore the random variables that define the various states of the Markov chain are discrete. In the SIR model, the elements of the population are classified into three states: Susceptible (S), Infected (I), and Recovered (R). The basic assumptions considered are: the population remains constant over time, those who make up the population go from susceptible to infected; people become infected regardless of age, sex, social status, etc. The population leaves the infected state recovering from the disease, and those who manage to do so acquire immunity and therefore can no longer be infected again. Several applications of Markov chains to COVID19 problem has been developed since the pandemic started, some of them can be found in [Albornoz, 2006, Marfak et al., 2020, Reynoso et al., 2020, Romeu, 2020]

4 Markov Chain Model

The model was motivated by the work developed by [Albornoz, 2006, Bernhardt, 2020, Romeu, 2020, Suarez et al., 2020]. In this work, the model considered is based on the information provided daily by the health authorities of the Mexican government. From the variables involved in the database, those considered to be analyzed are: infected, hospitalized, intensive care unit, intubated and those who unfortunately have passed away as a consequence of being infected by the SARS-Cov2 virus. With these variables, a data subset was constructed for Mexico City, including its delegations.



Figure 1: Covid Graphs for México

From a first review of the data on infections and accumulated cases, daily deaths, and totals, we obtained the graphs shown in the Figures 1 and 2, the case of the delegations in Mexico City is presented in Figure 3.

Locality	Population	Cases	Deaths	Hospitalized	Non-Hospitalized	UCI	Recovered	Intubated
CDMX	9018645	2867582	44829	119240	2748384	7694	2822795	16793
Azcapotzalco	408441	120044	3036	7610	112434	323	117008	1068
Milpa Alta	139371	62580	506	1388	61192	90	62074	225
Iztapalapa	1815551	517663	8810	21947	495716	1364	508853	3528
Tlalpan	682234	226018	2457	8073	217945	667	223561	1249
Xochimilco	418060	161640	1662	4934	156706	405	159978	772
MagContreras	245147	110230	894	2416	107814	176	109336	323
Gustavo A. Madero	1176967	345557	6759	16448	329109	905	338798	2246
Miguel Hidalgo	379624	101038	1770	5006	96032	377	99268	656
Iztacalco	393821	120927	2829	6992	113935	355	118098	868
Tlahuac	366586	147349	1343	3668	143681	255	146006	599
Coyoacan	621952	176323	3119	8778	167545	620	173204	1200
VCarranza	433231	145418	2496	6345	139073	422	142922	922
Cuajimalpa	199809	55683	640	1930	53753	138	55043	238
Cuauhtemoc	548606	173372	3003	7901	165471	565	170369	971
BJuarez	433708	121962	1693	5176	116786	416	120269	652
Alvaro O.	755537	281778	3809	10621	271157	615	277969	1276

Table 1: Official data for Mexico City and it's delegations

Based on the data analyzed, it is possible to determine the exact number of hospitalized patients (H), in one of the following conditions: Intensive Care Unit (U), Intubated (I) and Death (D), this can be illustrated in Figure 5, the values for each of the regions are given in Table 2.



Figure 2: Covid graphs for Mexico City



Figure 3: Cases for the Mexico City delegations



Figure 4: Deaths for the Mexico City delegations



Figure 5: Data for Hospitalized patients: U (UCI), I (Intubated), D (Dead)

5 Description of the model and numerical results

According to the information that can be extracted from the database, the state space for the Markov chain consists of six elements. Lets define the state space C

$$\mathcal{C} = \{S, E, H, U, I, D\}$$
(2)

where S corresponds to the susceptible population, E for those infected, H for those hospitalized, U for those in the Intensive Care Unit, I for intubated, and D for deceased. The representation is given in Figure 6.

Delegation	I	II	III	IV	V	VI	VII	VIII
CDMX	1830	27900	2193	1971	348	9086	3545	119240
Azcapotzalco	99	1924	98	64	18	764	142	7610
Coyoacan	125	2056	197	183	20	528	292	8778
Cuajimalpa	34	399	20	45	6	120	53	1930
Gustavo A.	235	4457	237	203	52	1391	415	16448
Iztacalco	74	1945	109	89	16	494	176	6992
Iztapalapa	285	5225	445	339	54	2058	686	21947
Magdalena C	58	425	64	43	7	148	68	2416
Milpa A	28	238	56	21	5	112	36	1388
Alvaro O	164	2384	148	154	29	706	268	10621
Tlahuac	54	756	87	64	7	318	130	3668
Tlalpan	145	1363	218	188	24	533	310	8073
Xochimilco	81	989	127	112	14	335	198	4934
Benito J	115	1108	68	132	9	292	160	5176
Cuauhtemoc	153	1949	117	135	46	488	231	7901
Miguel H	81	1066	59	78	20	321	198	5006
Venustiano C	99	1615	143	121	21	477	181	6345

Table 2: Hospitalization data for the City of Mexico and its delegations



Figure 6: Transition between states: S, E, H, U, F, I

The values used to determine the probability transition matrix are shown in Table 3, this values are obtained from Table 3 and Figure 5.

	S	Е	Н	U	Ι	F
S	9018645	-	-	-	-	-
E	-	2867624	-	-	-	-
H	-	-	119240	-	-	-
U	-	-	-	7694	5516	3893
Ι	-	-	-	-	16795	12631
F	-	-	-	-	-	44829

Table 3: Crossed values for Mexico City

As shown in Figure 6, the transition between the states that conform to the state space is assumed to take place per unit of time, this unit of time being one day. When a person enters into the dead state, cannot move to another state, while, a healthy person can continue to be healthy. The people who have recovered from the disease were intubated, or in the intensive care unit, are considered susceptible to getting the disease again, since having overcome the disease does not guarantee immunity and therefore they can get the disease again. The matrix P with the transistion probabilities is given by:

	/ 0.68	0.32	0	0	0	0	
	0.31	0.65	0.04	0	0	0	
D	0.66	0	0.08	0.01	0.02	0.23	
P =	0.49	0	0	0.20	0.26	0.05	
	0.25	0	0	0	0	0.75	
	\ 0	0	0	0	0	1	/

Once the matrix with the transition probabilities has been defined, we are interested in determining the transitions from one state to another after the following days 7, 15, 30, 45, 60, 90, 120, 180, 240, and 365, intending to study the evolution of the pandemic over time.

The results achieved for Mexico City are shown in Figures 7, 8, and 9. Figure 9 shows that, in the case of those who have been intubated, the probability of dying increases from 0.75 to 0.96. The probability of dying for people in the ICU increases from 0.31 to 0.81, this case is similar to that of hospitalized people. For infected persons, the probability of dying increases from 0.04 to 0.86. In Figure 7 can be observed that the probability of recovery for those who have been hospitalized goes from 0.37 to 0.0541 as time passes; the same results were found for people in the ICU. A special case is that of intubated patients, for whom the probability of recovery goes from 0.12 to 0.01, which means that as the disease evolves it is less likely to recover. These values are shown in Table 4.

For Mexico City, it can be seen that after 500 days since the pandemic arrived, large numbers of daily infections began to occur with values higher than four thousand infections per day. The same analysis was done for the sixteen delegations of Mexico City, the tables and graphs are presented in **Appendix A**.

Days	$E \curvearrowright F$	$H \curvearrowright F$	$U \curvearrowright F$	$I \curvearrowright F$	$H \curvearrowright U$	$U \curvearrowright I$	$H \curvearrowright I$	$H \curvearrowright S$	$U \curvearrowright S$	$I \curvearrowright S$
7	0.0394	0.2855	0.3102	0.7565	2.858e-04	3.433e-04	3.456e-04	0.3662	0.3539	0.1248
15	0.0795	0.3153	0.3390	0.7667	2.803e-04	3.273e-04	3.390e-04	0.3505	0.3384	0.1195
21	0.1085	0.3369	0.3598	0.7740	2.715e-04	3.169e-04	3.283e-04	0.3395	0.3277	0.1157
30	0.1503	0.3679	0.3899	0.7846	2.587e-04	3.021e-04	3.129e-04	0.3236	0.3124	0.1103
45	0.2157	0.4166	0.4368	0.8012	2.388e-04	2.788e-04	2.889e-04	0.2987	0.2883	0.1018
60	0.2760	0.4615	0.4801	0.8165	2.205e-04	2.574e-04	2.666e-04	0.2757	0.2661	0.0939
90	0.3831	0.5411	0.5570	0.8436	1.878e-04	2.193e-04	2.272e-04	0.2349	0.2268	0.0801
120	0.4744	0.6090	0.6226	0.8668	1.601e-04	1.869e-04	1.936e-04	0.2002	0.1932	0.0682
180	0.6184	0.7161	0.7259	0.9033	1.162e-04	1.357e-04	1.405e-04	0.1453	0.1403	0.0495
240	0.7229	0.7939	0.8010	0.9298	8.437e-05	9.850e-05	1.020e-04	0.1055	0.1018	0.0359
365	0.8578	0.8942	0.8979	0.9639	4.329e-05	5.055e-05	5.237e-05	0.0541	0.0523	0.0185

Table 4: Transition probabilities between states for several times

6 Conclusion

The pandemic worldwide, despite the efforts of scientists, governments, health authorities, and of course the population that has complied with sanitary and containment measures for almost a year, including vaccination, this enormous health problem does not seem to be over. The graphs show that as a consequence of vaccination, despite the increase in infections, deaths have no increased in the same way as in the first wave of the pandemic.

Based on the data, it can be seen that for Mexico City there are a total of 11920 infected persons with COVID19 who are hospitalized, of these, 3545 who were in intensive care and intubated lost their lives. With respect to the persons who were intubated (regions *III*, *IV*, *VI* and *VII*, in figure 5), those who were intubated and in the intensive care unit were 5516, and, of the intubated persons, 12631, unfortunately, passed away. From Figures 7, 8 and 9, can be concluded the following



Figure 7: Transition probabilities: Hospitalized to UCI, Hospitalized to Intubated, and UCI to Intubated state

Remarks 1 The probability of a hospitalized person being intubated in the intensive care unit is low, and the same is true for moving from the intensive care unit to intubation.

People in the intensive care unit, although they have a probability close to 0.3, as the days go by, it can grow to values close to 0.48 in the first 60 days.

The same occurs for people who are hospitalized; the probability of death in the first 7 days is 0.29, which increases to 0.46 in the first 60 days.

For intubated persons, the probability of death is 0.76 from the beginning and grows relatively low to 0.81 within 60 days.

For an infected person, if he/she does not manage to recover in the average time, 14 days, the probability of losing his/her life could become very high, when the probability of losing his/her life in the first days is very low.

In hospitalized persons and those in the intensive care unit, the probability of recovery goes from values close to 0.36 to 0.28 in the first 60 days, while intubated persons have a probability of recovery of 0.12 and decreases to 0.09 in the first 60 days. This means that the people who arrive at the hospital are either in delicate or very serious conditions.

At least in Mexico City, people do not consider attending hospitals as an option to receive care and prefer to stay at home even at the risk of losing their lives due to complications derived from the disease.

The COVID pandemic is not over, the consequences of the third wave in Mexico City have not been as devastating as it was in the first wave, i.e., hospitals have not been overwhelmed, the demand for medical oxygen has not reached



Figure 8: Transition probabilities to recovered state

the high levels observed months ago. However, local authorities have decided that the activities of a big city like Mexico City should be resumed, considering that the vaccination campaign is gradually advancing in all age groups and delegations. Notwithstanding, they also continue to emphasize the need to continue with the sanitary measures that were made known to the entire population from the beginning.

The delegations with higher number of infections and deaths are Iztapalapa, Gustavo A Madero, and Alvaro Obregon, this information can be corroborated in Table 1, also the corresponding tables for some of the delegations can be found in **Appendix A**.

For future work, it is planned to include in the analysis comorbidity conditions such as obesity, asthma, diabetes, pulmonary diseases, pneumonia, hypertension, among others, and determine the effects on COVID19 patients and their evolution in the states considered (hospitalized, intensive care unit, intubated, deaths). It is also important to know the current situation of infected persons and their relationship with age, i.e. young, adult, elderly and old. Finally, another issue being studied is the development of the pandemic taking into account the delegations with which it is surrounded.

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Figure 9: Transition probabilities to dead state

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Appendix A: Tables and graphs for delegations

The delegations with the highest number of cases and deaths are Iztalapapa (517,663 and 8,810), Alvaro Obregon (281,778 and 3,809), Gustavo A Madero (345,557 and 6,759), followed by Tlalpan (226,018 and 2,457), although the Coyoacan delegation has a record of 3,119 deaths due to covid19.

Analogous to the analysis provided for Mexico City, it can be observed that for the Iztapalapa delegation, there are 21947 hospitalized; those who were in intensive care and intubated were 686, intensive care and who died 740, intubated and who died 2744. The following can be observed

Remarks 2 For hospitalized patients, the likelihood of being admitted to the intensive care unit or being intubated, as well as the likelihood that those already in the intensive care unit will be intubated, for some delegations are

- Tlalpan: the probability of going from hospitalized to uni ranges from 0.00005 to 0.00015, from ICU to Intubated from 0.0001 to 0.00020, hospitalized to incubated from 0.0001 to 0.00025.
- Gustavo A. Madero: the probability of moving from hospitalized to ICU, from ICU to Intubated, and from inpatient to incubated ranges from 0.00005 to 0.00020, i.e., it is unlikely to move from one state to another.
- Alvaro O.: The probability of moving from hospitalized to ICU ranges from 0.00005 to 0.00007 with a maximum of 0.00015, the same is true for patients to be hospitalized as well as intubated.

Remarks 3 For the most affected delegations, those patients who are in some of the following states: Hospitalized, Intensive Care Unit, or intubated, the probability of death is

- Alvaro O.: of intubated patients from 0.78 to 0.9, ICU from 0.3 to 0.75, hospitalized patients from 0.3 to 0.75, and those infected from 0.1 to 0.7.
- Gustavo A. Madero: of intubated and hospitalized patients, the probability of death rises from 0.3 to 0.85, intubated patients rise from 0.8 to 0.9, while those who are infected, the probability of death rises from 0.1 in the first days and increases to 0.8 as time goes by.
- Iztapalapa: has a behavior similar to that of the Alvaro O delegation, but in this case, the probability of death exceeds 0.9, those hospitalized and in the ICU goes from 0.3 in the first 7 days to 0.9 as time goes by. Those infected ranges from 0.1 in the first days to a maximum of 0.8.
- Tlalpan: intubated persons range from a value close to 0.7 and grow to a value higher than 0.8, those in ICU grow from 0.3 to 0.65, hospitalized persons range from 0.2 to 0.6, while infected persons range from 0.1 in the first 7 days and grow to a value close to 0.6.

Finally,

Remarks 4 For the same delegations as above, for those patients who are in one of the following states: Hospitalized, Intensive Care Unit, or intubated, the probability of recovery is.

- Tlalpan: of hospitalized from 0.3 drops to 0.1, for those in ICU from 0.6 drops to values close to 0.2, while those who are only hospitalized drops from 0.7 to 0.3.
- Iztapalapa: of hospitalized from 0.2 drops to 0.05, for those in ICU from 0.5 drops to values close to 0.1, while those only hospitalized drops from 0.5 to 0.1.
- Gustavo A. Madero: for patients from 0.2 drops to 0.05, for ICU from 0.5 drops to values close to 0.1, while those only inpatients drop from 0.5 to 0.1
- Alvaro O.: Of hospitalized and ICU falls from 0.6 to 0.2, while those intubated falls from 0.2. to 0.1

This information can be corroborated in the graphs and tables below.

Days	$E \curvearrowright F$	$H \curvearrowright F$	$U \curvearrowright F$	$I \cap F$	$H \curvearrowright U$	$U \curvearrowright I$	$H \curvearrowright I$	$H \curvearrowright S$	$U \curvearrowright S$	$I \cap S$
7	0.03671	0.2060	0.2778	0.6754	5.451e-05	7.889e-05	8.227e-05	0.6955	0.6360	0.2837
15	0.0718	0.2129	0.2839	0.6783	1.250e-04	1.692e-04	1.888e-04	0.6166	0.5626	0.2517
21	0.0913	0.2204	0.2907	0.6814	1.526e-04	2.081e-04	2.304e-04	0.5816	0.5301	0.2375
30	0.1147	0.2334	0.3024	0.6867	1.724e-04	2.363e-04	2.604e-04	0.5492	0.5002	0.2244
45	0.1467	0.2568	0.3237	0.6962	1.806e-04	2.481e-04	2.728e-04	0.5188	0.4722	0.2120
60	0.1751	0.2803	0.3451	0.7059	1.785e-04	2.453e-04	2.696e-04	0.4988	0.4539	0.2038
90	0.2276	0.3258	0.3865	0.7244	1.684e-04	2.314e-04	2.543e-04	0.4661	0.4241	0.1905
120	0.2766	0.3685	0.4254	0.7419	1.578e-04	2.169e-04	2.386e-04	0.4365	0.3972	0.1784
180	0.3653	0.4459	0.4958	0.7735	1.385e-04	1.903e-04	2.091e-04	0.3829	0.3485	0.1565
240	0.4431	0.5139	0.5576	0.8013	1.215e-04	1.669e-04	1.835e-04	0.3360	0.3057	0.1373
365	0.5760	0.6298	0.6632	0.8487	9.251e-05	1.271e-04	1.397e-04	0.2558	0.2328	0.1046
120 180 240 365	0.2766 0.3653 0.4431 0.5760	0.3685 0.4459 0.5139 0.6298	0.4254 0.4958 0.5576 0.6632	0.7735 0.8013 0.8487	1.378e-04 1.385e-04 1.215e-04 9.251e-05	2.169e-04 1.903e-04 1.669e-04 1.271e-04	2.386e-04 2.091e-04 1.835e-04 1.397e-04	0.4365 0.3829 0.3360 0.2558	0.3972 0.3485 0.3057 0.2328	0.178

Table 5: Transition probabilities between states for several times

Days	$E \curvearrowright F$	$H \curvearrowright F$	$U \curvearrowright F$	$I \curvearrowright F$	$H \curvearrowright U$	$U \curvearrowright I$	$H \curvearrowright I$	$H \curvearrowright S$	$U \curvearrowright S$	$I \cap S$
7	0.0714	0.3165	0.3133562	0.8050	7.894e-05	1.076e-04	7.875e-05	0.5639	0.5706	0.16036
15	0.1316	0.3328	0.3293483	0.8097	1.583e-04	1.568e-04	1.579e-04	0.4832	0.4871	0.1376
21	0.1635	0.3488	0.3453244	0.8143	1.798e-04	1.793e-04	1.792e-04	0.4516	0.4546	0.1287
30	0.2031	0.3745	0.3711081	0.8216	1.874e-04	1.875e-04	1.867e-04	0.4221	0.4246	0.1203
45	0.2598	0.4170	0.4138643	0.8338	1.803e-04	1.806e-04	1.797e-04	0.3889	0.3910	0.1109
60	0.3112	0.4572	0.4542353	0.8452	1.687e-04	1.691e-04	1.682e-04	0.3614	0.3634	0.1031
90	0.4031	0.5295	0.5269798	0.8658	1.464e-04	1.467e-04	1.459e-04	0.3132	0.3149	0.0893
120	0.4826	0.5922	0.5900412	0.8837	1.269e-04	1.271e-04	1.264e-04	0.2714	0.2729	0.0774
180	0.6114	0.6937	0.6920639	0.9127	9.529e-05	9.548e-05	9.497e-05	0.2039	0.2050	0.0581
240	0.7081	0.7699	0.7686971	0.9344	7.158e-05	7.172e-05	7.133e-05	0.1531	0.1540	0.04367
365	0.8392	0.8733	0.8725719	0.9639	3.944e-05	3.951e-05	3.929e-05	0.0844	0.0848	0.0241
	Table 6: Transition probabilities between states for several times. Gustavo A Made									

Days	$E \cap F$	$H \curvearrowright F$	$U \curvearrowright F$	$I \curvearrowright F$	$H \curvearrowright U$	$U \curvearrowright I$	$H \curvearrowright I$	$H \curvearrowright S$	$U \curvearrowright S$	$I \cap S$
7	0.05599	0.2884	0.3155	0.7790	9.866e-05	1.873e-04	0.00014	0.5399	0.5254	0.1669
15	0.1031	0.3068	0.3327	0.7847	1.795e-04	2.422e-04	0.00025	0.4508	0.4355	0.1398
21	0.1301	0.3237	0.3489	0.7900	1.951e-04	2.645e-04	0.00027	0.4229	0.4077	0.1312
30	0.1662	0.3499	0.3742	0.7982	1.964e-04	2.668e-04	0.00028	0.3989	0.3842	0.1239
45	0.2212	0.3924	0.4150	0.8113	1.858e-04	2.526e-04	0.00026	0.3710	0.3572	0.1152
60	0.2722	0.4322	0.4533	0.8237	1.738e-04	2.363e-04	0.00025	0.3466	0.3336	0.1076
90	0.3645	0.5041	0.5226	0.8460	1.518e-04	2.064e-04	0.00021	0.3026	0.2913	0.0939
120	0.4451	0.5670	0.5832	0.8656	1.326e-04	1.802e-04	0.00019	0.2642	0.2544	0.0821
180	0.5768	0.6698	0.6821	0.8975	1.011e-04	1.374e-04	0.00014	0.2015	0.1939	0.0626
240	0.6773	0.7482	0.7576	0.9218	7.708e-05	1.048e-04	0.00019	0.1536	0.1479	0.0477
365	0.8166	0.8568	0.8622	0.9556	4.382e-05	5.957e-05	0.00006	0.0873	0.0841	0.0271

Table 7: Transition probabilities between states for several times, Iztapalapa



Figure 10: Transition probabilities from Infected, Hospitalized, UCI and Intubated to Death state for delegations: Azcapotzalco, Coyoacan, Cuajimalpa, Gustavo Madero, Iztacalco, Iztapalapa, Magdalena C. and Alvaro O.



Figure 11: Transition probabilities from Infected, Hospitalized, UCI and Intubated to Death state for delegations: Benito J., Miguel H., Milpa A., Tlahuac, Tlalpan, Xochimilco, Venustiano C. and Cuauhtemoc



Figure 12: Transition probabilities from hospitalized, UCI and Intibated to Recovered state for delegations: Azcapotzalco, Coyoacan, Cuajimalpa, Gustavo Madero, Iztacalco, Iztapalapa, Magdalena C., and Alvaro O.



Figure 13: Transition probabilities from hospitalized, UCI and Intibated to Recovered state for delegations: Benito J., Miguel H., Milpa A., Tlahuac, Tlalpan, Xochimilco, Venustiano C. and Cuauhtemoc



Figure 14: Transition probabilities from hospitalized and UCI to intubated state for delegations: Azcapotzalco, Coyoacan, Cuajimalpa, Gustavo Madero, Iztacalco, Iztapalapa, Magdalena C. and Alvaro O.

Days	$E \curvearrowright F$	$H \curvearrowright F$	$U \curvearrowright F$	$I \curvearrowright F$	$H \curvearrowright U$	$U \curvearrowright I$	$H \curvearrowright I$	$H \curvearrowright S$	$U \curvearrowright S$	$I \cap S$
7	0.0481	0.2581	0.2941	0.7639	5.676e-05	5.839e-05	5.518e-05	0.6307	0.6034	0.2002
15	0.0918	0.2683	0.3036	0.7672	1.241e-04	1.146e-04	1.219e-04	0.5480	0.5230	0.1742
21	0.1159	0.2789	0.3136	0.7706	1.471e-04	1.370e-04	1.447e-04	0.5136	0.4896	0.1633
30	0.1454	0.2966	0.3304	0.7762	1.608e-04	1.505e-04	1.584e-04	0.4824	0.4595	0.1534
45	0.1869	0.3275	0.3598	0.7861	1.625e-04	1.524e-04	1.602e-04	0.452	0.4301	0.1437
60	0.2243	0.3578	0.3886	0.7957	1.571e-04	1.474e-04	1.548e-04	0.4294	0.4088	0.1366
90	0.2933	0.4147	0.4428	0.8138	1.436e-04	1.348e-04	1.4158e-04	0.3908	0.3721	0.1243
120	0.3559	0.4666	0.4923	0.8303	1.309e-04	1.228e-04	1.290e-04	0.3561	0.3390	0.1133
180	0.4652	0.5571	0.5783	0.8591	1.087e-04	1.020e-04	1.072e-04	0.2958	0.2816	0.0941
240	0.5559	0.6322	0.6498	0.8829	9.028e-05	8.472e-05	8.899e-05	0.2456	0.2338	0.0781
365	0.6984	0.7502	0.7622	0.9205	6.13e-05	5.753e-05	6.043e-05	0.1668	0.1588	0.0531
	Table 8: Transition probabilities between states for several times, Alvaro Ot									

Cable 8: Transition probabilities between st	tates for several tin	nes, Alvaro Obregon
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Figure 15: Transition probabilities from hospitalized and UCI to intubated state for delegations: Benito J., Miguel H., Milpa A., Tlahuac, Tlalpan, Xochimilco, Venustiano C. and Cuauhtemoc