# Robustness analysis in an inter-cities mobility network: modeling municipal, state and federal initiatives as failures and attacks toward SARS-CoV-2 containment

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## ABSTRACT

~~Motivated by the challenge related to the COVID-19 pandemic and the seek for optimal containment strategies,~~ we present a robustness analysis ~~into~~ an inter-cities mobility complex network. Brazilian data from 2016 are used to build a network with more than five thousand cities and twenty-seven states with the edges representing the weekly flow of people between cities. The municipal initiatives are abstracted as nodes' failures and federal actions as targeted attacks. Our results reveal that individual municipalities' actions do not cause a high impact on mobility restraint since they tend to be punctual and disconnected to the country scenario. Oppositely, the coordinated isolation of specific cities is key to detach entire network areas and thus prevent ~~a~~ spreading ~~process to prevail.~~ Networks' centrality measures like strength, degree, betweenness, and topological vulnerability are used to guide the attacks, which pose better results than simply reacting to the pandemic by isolating ~~the~~ cities according to the temporal order in which the first case of COVID-19 is documented.

## INTRODUCTION

Since early 2020, the virus SARS-CoV-2 quickly spread to the entire world and became a pandemic in a short time. As of May 26th, 2020, the pandemic has reached more than 200 countries, with more than 5,678,128 confirmed cases of COVID-19, the disease caused by the virus, and about 351,654 deaths, globally (Worldometer, 2020). In Brazil, there are more than 393,542 confirmed cases and nearly 24,568 deaths, with the first documented case located in the city of São Paulo on February 25th, 2020 (Cota, 2020).

The design of containment strategies promoted in federal and municipal actions became a large challenge to prevent community transmission. As the coordinated isolation of specific cities is key to prevent ~~a~~ spreading ~~process to prevail~~, the analysis of the inter-cities terrestrial mobility network is useful for decision making.

The complex network approach (Estrada, 2012) emerges as a natural mechanism to treat mobility data, taking areas as nodes and movements between origins and destinations as edges (Barbosa et al., 2018). A complex network can be seen as a graph (set of nodes and relations between them) representing a complex system. A mobility network is, therefore, a set of areas and a representation of the flow of people between each possible pair of areas (Santos et al., 2019a).

The structure of the underlying network of a system reveals its ability to survive to failures and coordinated attacks. One important question is ~~to know~~ how many nodes can be removed until the network completely fragments into small pieces (Barabási et al., 2016). In this paper, we present a robustness analysis (Barabási et al., 2016; Callaway et al., 2000) on mobility complex networks, ~~motivated by the challenge related to the COVID-19 epidemic and the seek for proper~~ containment strategies.

Within the context of ~~the~~ robustness analysis, the local/municipal initiatives are here modeled as failures and the federal's as attacks. We present strategies to effectively damage the network structure by choosing the cities (or states) that have more impact on mobility. The local initiatives are considered failures because they are sometimes disconnected from the federal ones. It is possible that some cities start to care about an epidemics before the others, and/or before the country itself, either because their mayors have more political influence than the average, or due to local popular pressure. In both cases, the outcome for the city is likely to diverge from the announced measures for the country.

Contrarily, the coordinated attacks in the mobility network are considered to be federal actions due to its global scale characteristics. As the entire network is subjected to ~~the~~ federal rules, the state has the power to pick specific nodes, either to invest in infrastructure because of its potential flow for supplies, to diminish natural disaster risks, or to isolate them from the rest in a disease outbreak. The isolation of a city consists of either closing the borders to other municipalities, as performed in Wuhan, China (Li et al., 2020a), or to make the social distancing policy more rigorous.

The IBGE data from 2016 (IBGE - Instituto Brasileiro de Geografia e Estatística, 2017) is employed in the present study. The data contains the flow of ~~buses, vans, and similar~~ transports between cities, considering only terrestrial vehicles from companies that sell tickets to passengers. Another data source, commonly used ~~in the research of this nature,~~ is the pendular travels (IBGE - Instituto Brasileiro de Geografia e Estatística, 2020) of people moving from home to work/study. Yet, the former is more recent and captures the flows of people between all pairs of Brazilian cities in a more general scenario. The information collected ~~by the data we are using seeks to~~ quantify the interconnection between cities, the movement of ~~attraction that~~ urban centers ~~carry out for the consumption of goods and services~~, and the long-distance connectivity ~~of~~ Brazilian cities.

Our contributions are the robustness analysis of the Brazilian inter-cities mobility network with the abstraction of nodes' failures as municipalities' actions and targeted attacks as federal's. We assess the network impacts during nodes' removal ~~through~~ two metrics: ~~the first is~~ the giant component size and ~~the second is~~ the total remaining flow within the network. The targeted attacks are guided by centrality measures ~~of the networks~~, such as degree, betweenness, and vulnerability. The results are compared to the so-called reactive strategy, which consists of the removal of cities according to the temporal order in which they document the first case of COVID-19.

## MATERIALS AND METHODS

Complex networks are a ~~natural mechanism~~ to treat mobility data, taking areas as nodes and movements between origins and destinations as edges. Formally, a network is defined as an undirected graph $G(V,E)$, consisting of the set $V$ of vertices (or nodes) and set $E$ of edges, with the total number of nodes $N = |V|$ and the total number of edges $|E|$. The edges' weights are represented as the matrix $W = \{w_{ij}\}$, for $i, j = 1, \cdots, N$, so that $w_{ij}$ is the weight between edges $i$ and $j$. The mean value and standard deviation of this matrix are $\overline{w}$ and $\sigma$, respectively.

The flows (weights) from the network (IBGE - Instituto Brasileiro de Geografia e Estatística, 2017) are here aggregated within the round trip, which means that the number of travels from city A to city B is the same as from B to A. We produce three types of undirected networks with a different number $N$ of nodes to capture actions in different scales (country and state):

1. $N = 5420$ - Brazil (BR): nodes are cities and edges are the flow of direct travels between them. Almost all Brazilian cities are considered in the dataset ~~(IBGE - Instituto Brasileiro de Geografia e Estatística, 2017)~~.

2. $N = 620$ - São Paulo state (SP): a subset of the previous network, containing only cities within the São Paulo state.

3. $N = 27$ - Brazilian states (BS): in contrast with the others, in this network, each state is a node and the edges are the accumulated flows between them.

Several networks are analyzed from the three models (BR, SP, and BS). Thresholds are employed to neglect travels in three levels: i) original data with all recorded flow, ii) only edges of at least an average flow and, iii) a more restricted topology with the higher flows. The chosen thresholds are $\eta_0 = 0$, $\eta_1 = \overline{w}$ and $\eta_2 = \overline{w} + \sigma$. Edges with flows below these values are discarded. We thus end up with nine networks in total as described in Table 1, where $N$ is the size of the network, and $|E|$ is the number of edges/links. The motivation behind the threshold levels is the fact that most centrality measures ~~we employ~~ do not account for the flows and thus consider all edges with the same importance. Besides, neglecting some small flow connections may help to approximate the network measures to the real spreading dynamics of SARS-CoV-2 (Freitas et al., 2020).

**Table 1. Networks' statistics**. The Brazilian (BR), São Paulo state (SP), and Brazilian states (BS) networks, with three flow thresholds: $\eta_0 = 0$, $\eta_1 = \overline{w}$ and $\eta_2 = \overline{w} + \sigma$, where $\overline{w}$ is the average flow and $\sigma$ is the standard deviation.

| | Network | | |
|---|---|---|---|
| | BR | SP | BS |
| $N = \|V\|$ | 5420 | 620 | 27 |
| $\overline{w}$ | 48.04 | 73.20 | 2032.29 |
| $\sigma$ | 100.21 | 122.79 | 4397.86 |
| $\|E\|$ for $\eta_0$ | 65264 | 9592 | 474 |
| $\|E\|$ for $\eta_1$ | 15505 | 2610 | 108 |
| $\|E\|$ for $\eta_2$ | 4217 | 758 | 44 |

## Measures of complex networks

The topological degree $k$ of a node presents ~~a local notion of~~ connectivity: it is the number of edges it has to other nodes. The networks ~~under investigation~~ are undirected with no distinction between incoming and outgoing edges. On the other hand, the betweenness centrality captures the importance of a node ~~in a broader sense~~. Between any pairs of nodes $l$ and $m$ of a connected network, there is at least one shortest path, and the betweenness $b_i$ is the rate of such paths that pass through $i$:

$$b_i = \sum_{l \neq m \neq i} \frac{g_{lm}(i)}{g_{lm}}, \tag{1}$$

in which $l, m, i \in V$, $g_{lm}$ is the total number of shortest paths (or geodesic paths) between $l$ and $m$, and $g_{lm}(i)$ are those that pass through $i$.

The efficiency $e_{ij}$ in the communication between a pair of nodes $i$ and $j$ can be defined as the inverse of the shortest path length between them, and the network efficiency $\mathscr{E}$ is

$$\mathscr{E} = \frac{\sum_{i \neq j} e_{ij}}{N(N-1)}, \tag{2}$$

the average of all efficiencies, with $i, j \in V$. The vulnerability index $\mathscr{V}_i$ (Santos et al., 2019c,b), quantifies how vulnerable a network is when a certain node $i$ is deleted:

$$\mathscr{V}_i = \frac{\mathscr{E} - \mathscr{E}_i^*}{\mathscr{E}}, \tag{3}$$

in which $\mathscr{E}_i^*$ is the average network efficiency after the removal of node $i$. In brief, the flow of information is considered more efficient in networks with small shortest path lengths.

The strength $s_i$ of a node is the accumulated flow from incident edges:

$$s_i = \sum_{j=1}^{N} w_{ij}. \tag{4}$$

~~Within the scope of the present work,~~ the degree is the number of cities (or sates) that a city (state) is connected to, showing the number of possible destinations for the SARS-CoV-2. The betweenness centrality, ~~on the other hand,~~ considers the entire network to depict the topological importance of a city in the routes ~~that are~~ more likely to be used. The vulnerability accounts for the impact in the network efficiency when a certain city is isolated. Lastly, the strength captures the total number of people that travel to (or come from) such places in a week. From a probability perspective, the cities that receive more flow of people are more vulnerable to SARS-CoV-2.

### Robustness

The robustness of a network is its capacity ~~of keeping~~ connected even after the removal of nodes and/or edges. An energy drop reaching some computers in computer networks, or a car accident on an important road, are usually not predictable events that depend on several internal and/or external causes, thus characterizing a system failure. Conversely, a node may be intentionally removed to disrupt the network structure, typifying an attack.

We propose strategies to identify the municipalities that play a key role in mobility. First, the network response to random failure is assessed as a baseline to compare with the attacks. Our motivation is the fact that real networks are robust to random failures but are fragile to attacks (Barabási et al., 2016; Callaway et al., 2000; Cohen et al., 2000; Iyer et al., 2013).

The main question is to figure out how many and which nodes must be removed until the network collapses. ~~This being said,~~ understanding which cities are important for mobility to ~~either invest in infrastructure to enhance their capacity or to~~ know exactly which node should be isolated in a disease outbreak is of major interest.

The measure ~~we use~~ to quantify the network response to both failures and attacks is the number of nodes in the giant component $P_\infty(f)$ when a certain rate $f$ of nodes is removed. Further, as the underlying networks have flows between nodes, the total remaining flow $\|W\| = \sum_{ij} w_{ij}$ is computed as well. The flow present in the network after the removal of a rate $f$ of nodes is $\|W\|(f)$. Whether it remains connected or not is thus captured by $P_\infty(f)$ and $\|W\|(f)$, whose values decrease for increasing $f$.

Choosing the proper node to be removed is crucial and can be done in different ways. Failures are the trivial case, for which a node is randomly selected. However, coordinated attacks demand some strategy such as always removing the nodes with higher degrees. We propose four strategies: deleting nodes with a higher degree ($\max k$), betweenness ($\max b$), vulnerability ($\max \mathscr{V}$), and strength ($\max s$). Attacks oriented by higher degrees are effective and produce better results than non-local measures in most cases (Iyer et al., 2013).

The BR network ($N = 5420$) has a degree distribution that follows a power-law with coefficient $\gamma = 2.57$, which characterizes a scale-free topology. This means that, under random failures, the critical threshold $f_c = 0.9911$, for $f_c = 1 - (1/(\kappa - 1))$ with $\kappa = \langle k^2 \rangle / \langle k \rangle$, gives the exact fraction of node removals that break the network. This represents a structure that is strongly robust to failures, i.e., almost all nodes must be removed before the giant component is dismantled (Barabási et al., 2016).

On the other hand, such networks are vulnerable to attacks, especially when they are targeted to higher degree nodes (hubs). Within this context, we consider random failures as isolated mitigation actions by some city or state, and the attacks as federal actions, ~~considering the "big picture"~~. ~~Regarding mobility networks, some cities are key to an outbreak disruption. Consider for instance the isolation of Wuhan in the restrain of COVID-19 spread in China (Li et al., 2020a). Isolating São Paulo or employing a more rigid policy for social distancing when the first cases appeared could have substantially reduced the spreading in Brazil.~~

~~The~~ robustness is measured by

$$R = \frac{1}{N} \sum_{i=1}^{N} \frac{\Gamma(i/N)}{\Gamma(0)}, \tag{5}$$

for $R \in (0, 1/2)$ and $\Gamma(i/N)$ is the robustness measure when a fraction $i/N$ of the nodes are removed. The higher the $R$, the more robust the network is according to the function $\Gamma$, which could be either $P_\infty$ or $\|W\|(f)$. Note that the normalization factor $1/N$ allows different size networks to be compared to each other. For $P_\infty$, the minimum value $R = 1/N$ is reached with the star-like topology and the maximum $R = \frac{1}{2}(1 - 1/N)$ with the complete graph.

# RESULTS

~~This section presents the results of the robustness analysis in the previously mentioned networks. Table 2 exhibits their average degree $\langle k \rangle$, average betweenness $\langle b \rangle$, average strength $\langle s \rangle$, and average vulnerability $\langle \mathscr{V} \rangle$ for the Brazilian (BR), São Paulo state (SP), and Brazilian states (BS) networks under flow thresholds $\eta_0, \eta_1$ and $\eta_2$. As stated, the nodes are connected when between them there is a nonzero flow. Figure 1 presents illustrations of the BR network under $\eta_1$ and $\eta_2$. The total number of nodes is the same, however, the total number of edges, average degree $\langle k \rangle$, average betweenness $\langle b \rangle$ and average strength $\langle s \rangle$ decrease and average vulnerability $\langle \mathscr{V} \rangle$ increases for increasing connection thresholds ($\eta$) - see Tables 1 and 2.~~

**Table 2. Networks' measures**. Average degree $\langle k \rangle$, average betweenness $\langle b \rangle$, average strength $\langle s \rangle$ and average vulnerability $\langle \mathscr{V} \rangle$ for the Brazilian (BR), São Paulo state (SP), and Brazilian states (BS) networks under flow thresholds $\eta_0, \eta_1$ and $\eta_2$.

| | Network | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | $\eta_0$ | | | $\eta_1$ | | | $\eta_2$ | | |
| | BR | SP | BS | BR | SP | BS | BR | SP | BS |
| $\langle k \rangle$ | 24.08 | 15.47 | 17.56 | 5.72 | 4.21 | 4.0 | 1.56 | 1.22 | 1.63 |
| $\langle b \rangle$ | 5574.09 | 504.24 | 4.56 | 4828.08 | 397.67 | 13.04 | 2177.91 | 125.7 | 6.41 |
| $\langle s \rangle$ | 1156.86 | 1132.35 | 35677.91 | 845.23 | 813.66 | 30162.76 | 504.93 | 473.9 | 21043.46 |
| $\langle \mathscr{V} \rangle$ | 4.18E-4 | 3.62E-3 | 7.57E-2 | 4.97E-4 | 4.6E-3 | 8.11E-2 | 6.95E-4 | 6.53E-3 | 0.1 |

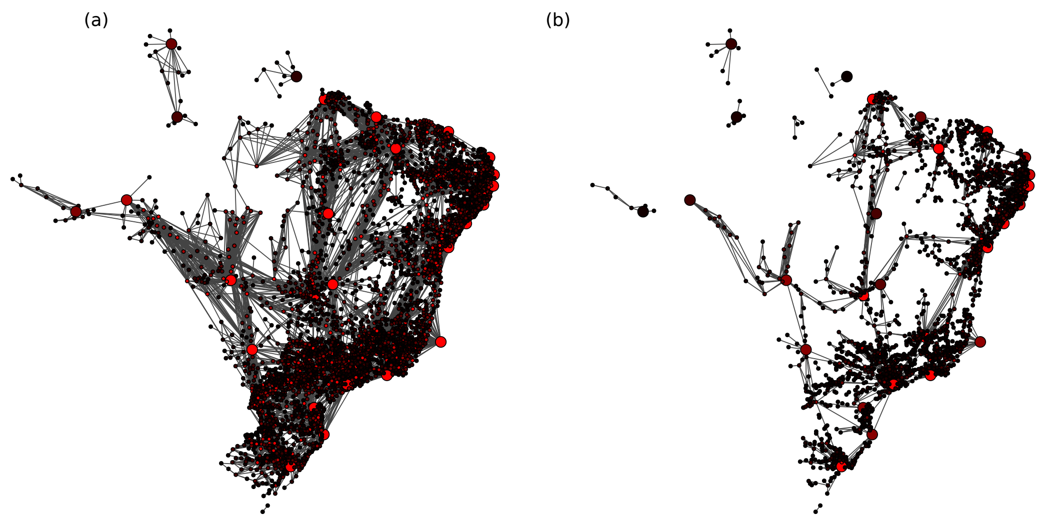


**Figure 1. Brazilian mobility network (BR) under a) $\eta_1$ and b) $\eta_2$.** The larger nodes are state capitals. Those with smaller degrees are black and the ones with higher degrees are red. The figure for $\eta_0$ is not properly visible with its 65254 edges.

~~According to the available data of the notified cases from daily state bulletins of the Brazilian Health Ministry~~ (Cota, 2020), until May 26th, 2020, the number of cities with at least one confirmed patient with COVID-19 is 3865 ($f = 0.71$) in Brazil and 505 ($f = 0.81$) in the state of São Paulo.

~~Figure 2 exhibits the results of the robustness analysis in the Brazilian network under thresholds $\eta_0$, $\eta_1$, and $\eta_2$ and the reactive strategy of removing the cities with documented cases of COVID-19 following the temporal sequence (red 'x' symbol). The first line presents the size of the giant component $P_\infty(f)$ for different node removal strategies, and the second pictures the total remaining flow within the system $\|W\|(f)$. The lefthand pictures correspond to the network built directly from the original data ($\eta_0$), and the rightmost ones are the least connected ($\eta_2$).~~

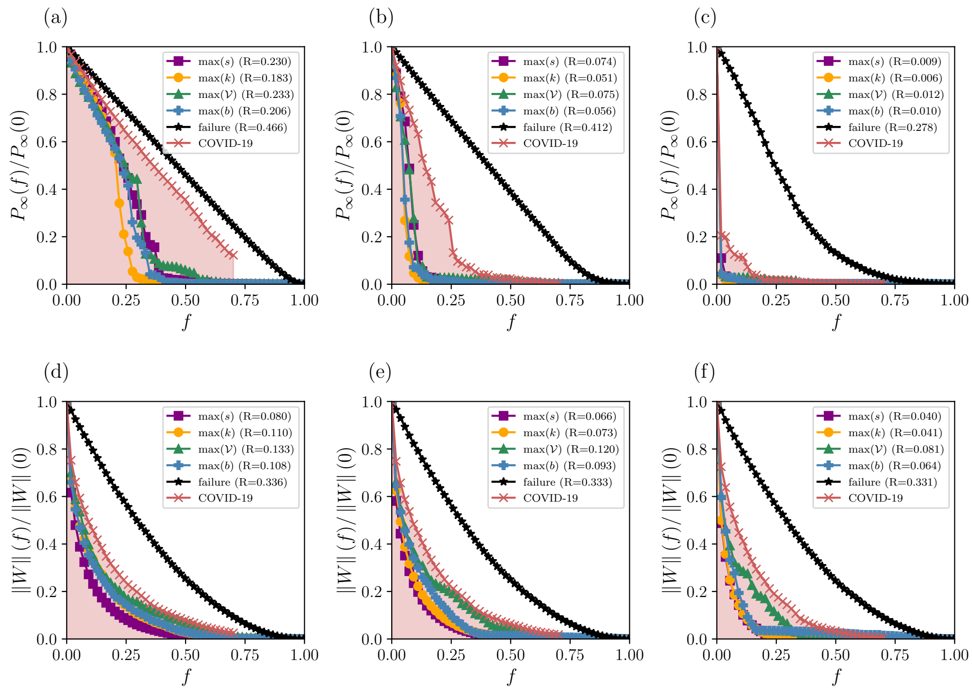


**Figure 2. Robustness analysis for the Brazilian mobility network (BR).** Three thresholds are considered: a,d) $\eta_0$; b,e) $\eta_1$; and c,f) $\eta_2$, as in Table 1. The first line exhibits the rate of removed nodes $f$ versus the normalized size of the giant component $P_\infty(f)/P_\infty(0)$ and the second gives the normalized remaining flow in the system $\|W\|(f)/\|W\|(0)$. Approximately $f = 0.71$ nodes have documented cases of COVID-19.

~~There are~~ some cities ~~in which~~ cases of COVID-19 have not been ~~registered~~ yet by May 26th, 2020, therefore, it was not possible to calculate the $R$ associated with the reactive strategy - $f \in [0, 0.71]$. However, ~~based on Figure 2, it is clear that it presents~~ an intermediate performance, amid failures and targeted attacks up to $f = 0.71$. It is better regarding the remaining flow (bottom of Figure 2) than to the size of the giant component (upper part of Figure 2). This means that isolating cities with documented cases of COVID-19 has a low impact on the number of connected cities in the larger component, but the effect in the remaining flow is strong. There is an important feedback mechanism in this case: the emergence of COVID-19 cases is possibly associated with both imported cases ~~(from abroad)~~ and community transmission between cities in the country. Thus, the flow of people is on both sides of this relation.

The São Paulo mobility network (SP) produces similar results as the BR's (Figure 3). The main differences are that ~~now~~ the reactive strategy is closer to the other attacking strategies for the two evaluation measures and the networks take longer to break. ~~Besides,~~ the vulnerability measure ($\mathscr{V}$) starts to play a ~~better~~ role than in the previous network, being the second-best under $\eta_0$ and $P_\infty$.

The differences between failures and attacks are only noticeable for higher thresholds in the network formed by the Brazilian states (BS) - see Figure 4. Removing nodes with the attacking strategies does not cause more impact than picking by chance under $\eta_0$ and $P_\infty$. The results ~~become to~~ differ for other thresholds when the shortest paths between nodes increase and the reactive strategy has enhanced performance.

~~Note~~ that some plateaus represent regions where the removal of some nodes does not impact ~~on~~ robustness. ~~Refer,~~ for example, ~~to~~ the interval $f \in [0.2, 0.75]$ in Figure 4c, where attacking nodes under the betweenness guidance does not cause any harm, because the referred nodes do not belong to the giant component. Interestingly, in Figure 4 the attacks and failures perform similarly and sometimes the failures are even more effective - ~~check the reactive strategy for $f = 0.5$ at~~ Figure 4b ~~and betweenness for $f = 0.1$ at~~ Figure 4d. ~~For the second line of Figure 4,~~ the strategies follow the same order of efficacy under all thresholds: strength, degree, vulnerability, and betweenness, with strength being the best and betweenness

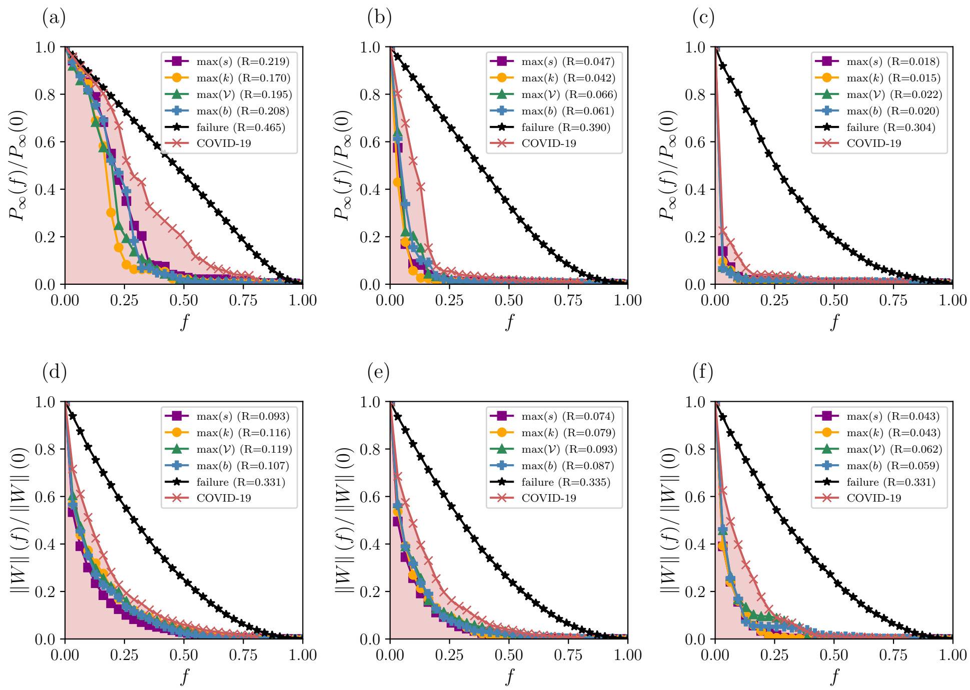


**Figure 3. Robustness analysis for the São Paulo mobility network (SP).** Three thresholds are considered: a,d) $\eta_0$; b,e) $\eta_1$; and c,f) $\eta_2$, as in Table 1. The first line exhibits the rate of removed nodes $f$ versus the normalized size of the giant component $P_\infty(f)/P_\infty(0)$ and the second gives the normalized remaining flow in the system $\|W\|(f)/\|W\|(0)$. Approximately $f = 0.81$ nodes have documented cases of COVID-19.

the worst. The reactive strategy is even better than betweenness for $\eta_0$.

~~Some transitions occur between the three Figures.~~ Considering the robustness evaluation with $P_\infty$, there is an increasing importance of the vulnerability measure ~~from Figure 2 to Figure 4.~~ Besides, while the degree is the best measure to guide the attacks ~~in Figures 2 and 3,~~ it is not for the BS, where vulnerability and betweenness have more importance. ~~Alike,~~ ~~for the bottom part of the Figures 2 and 3,~~ the strength is the leading measure for attacks, and vulnerability is the worst. ~~Oppositely,~~ although strength is also the best ~~in the bottom of Figure 4~~, betweenness is now the worst.

## DISCUSSION

All measures (degree, betweenness, vulnerability, and strength) for the BR network exhibit the cities of São Paulo and Belo Horizonte within the top-five higher values and most present Campinas and Brasília. Concerning the SP network, the measures rank the cities of São Paulo, Campinas, São José do Rio Preto and Ribeirão Preto within the top-five values as well. Differently, the BS network does not display a clear pattern for the degrees, but the states of São Paulo and Minas Gerais come out in the first positions for betweenness, vulnerability, and strength. The cities from the state of São Paulo that have higher values are also cited in recent studies (Freitas et al., 2020; Guimarães Jr et al., 2020) on the most vulnerable cities to COVID-19 due to their intense traffic of people.

As expected (Barabási et al., 2016), random failures do not break the network until almost all nodes are removed, due to its scale-free structure, and all targeted attacks dismantle the networks for small $f$, except for the reactive strategy ~~in Figure 2a~~. The higher the threshold, the fewer nodes must be removed to break the network structure, since the giant component is initially smaller than with $\eta_0$. ~~Still in Figure 2a,~~ the $R$ measure, ~~from Equation (5),~~ shows that the more effective attack strategy for $P_\infty$ is guided by degree, and by strength for $\|W\|(f)$ for all thresholds. The smaller the $R$ is, the more destructive is the corresponding attack strategy. The vulnerability index is the worst in all networks for both evaluation

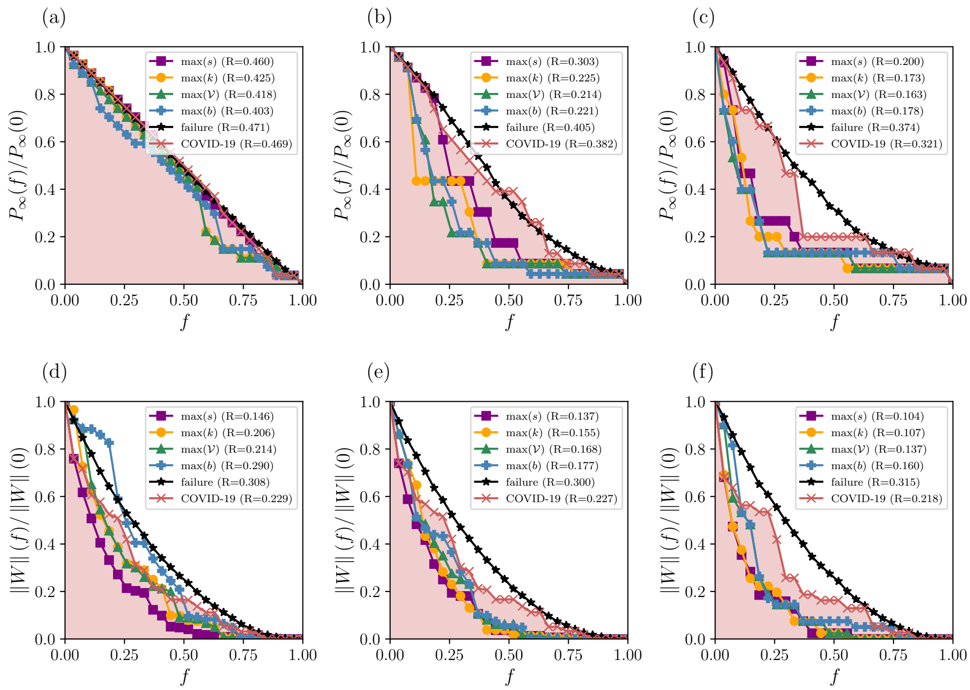

**Figure 4. Robustness analysis for the Brazilian states' mobility network (BS).** Three thresholds are considered: a,d) $\eta_0$; b,e) $\eta_1$; and c,f) $\eta_2$, as in Table 1. The first line exhibits the rate of removed nodes $f$ versus the normalized size of the giant component $P_\infty(f)/P_\infty(0)$ and the second gives the normalized remaining flow in the system $\|W\|(f)/\|W\|(0)$.

functions.

When the flows are evaluated, the strength is more effective to guide the attacks in all scenarios. The reactive strategy produces a similar impact on decreasing the flow of people, although slightly worse, and the number of remaining connected cities is always higher. Therefore, despite reacting to the disease spreading is a valid action, targeted attacks under network measures like strength provide better results in terms of the size of the giant component and remaining flow in the system.

Quickly breaking the transmission network is important to contain any highly contagious disease. The rapid implementation of control measures such as travel restrictions, ~~suspension of intracity public transport, closing entertainment venues, and banning public gatherings drastically reduced the number of potential cases of COVID-19 in China.~~ Cities that preemptively adhered to the measures reported fewer cases than the others and the virus reached them later (Tian et al., 2020). The city of Wuhan was the main focus in China and the complete isolation of the area was vital to mitigate the virus spreading (Li et al., 2020a). On the other hand, the rest of the world received the SARS-CoV-2 concurrently at different places and had to divide efforts to restrain it. Our strategy ranks ~~the~~ cities according to their importance on connectivity and flow of people and serves to guide which places should have more immediate government attention.

The targeted attacks are important especially in areas where people are not sufficiently tested for COVID-19 since the reactive strategy strongly depends on effective epidemic surveillance. Li et al. (2020b) estimate that 86% of infections were undocumented in China before the travel restrictions of January 23rd, 2020, and the undocumented infections were the source of 79% of the documented cases. Underreporting is also present in Brazil, as Hallal et al. (2020) points out in a seroprevalence survey they conducted nationwide.

The US response to COVID-19 is mostly guided by Governors and Mayors primarily because of their political system. Korea and Taiwan implemented a centralized national strategy instead (Haffajee and Mello, 2020). Canada has the Health Portfolio Operations Centre (HPOC), which concentrates the operations at different levels of government. The Organisation for Economic Co-operation and Development

OECD (2020) argues that coordinated response across regions and states minimize coordination failures as the "pass the buck" behavior is avoided.

Federal initiatives towards SARS-CoV-2 containment are more effective in breaking the transmission network than leaving the cities (or states) on their own. We have shown that random failures usually take longer to dismantle the networks than choosing the nodes with some criteria. Besides, ~~the~~ network measures provide a good approximation ~~to~~ the emergence of COVID-19 (Freitas et al., 2020). With a coordinated operation scheme, the different organizational levels of government can implement isolation or more rigid physical distancing policies in specific cities/states that are key to restrain the virus spreading.

## CONCLUSIONS

~~We present a robustness analysis into terrestrial inter-cities mobility networks with the abstraction of municipal initiatives as nodes' failures and the federal actions as targeted attacks. The networks are built with the IBGE mobility data that contains the flow of buses, vans, and similar transports between cities, considering only terrestrial vehicles from companies that sell tickets to passengers.~~

~~Cities (or states) are modeled as nodes in the network and the connections are mediated through the mobility data. The isolation of certain nodes is extremely relevant to spreading process containment. The question we address in the paper is to determine what are the most important nodes that keep the network connected. We consider three scenarios: the whole network with the Brazilian cities ($N = 5420$), another with the cities of the São Paulo state only ($N = 620$), and lastly the network formed by the Brazilian states ($N = 27$ ), each as a node.~~

~~The abstraction we make is to consider the random removal of nodes (failures) as cities' individual initiatives, that do not have a connection to the country policies. Conversely, the attacks are isolation measures determined by the federal government and applied at a municipality level. Such attacks are performed according to some node metrics such as degree, betweenness, vulnerability, and strength. Moreover, we perform attacks following the list of cities that have documented cases of COVID-19 in the temporal order the cases appeared. This is the so-called reactive strategy, a possible action that the Health Ministry could employ by isolating the cities whenever the first patient with the disease appears.~~

~~We performed the analysis with each network in three instances, considering different thresholds for the flows. The first instance comprehends all links with nonzero flows, the second contains edges with flows above a certain average value, and lastly the flows above a high threshold. The motivation for the flow levels is the fact that some centrality measures we employed do not account for the flows and thus consider all edges with the same importance.~~

~~The robustness of the networks is evaluated according to two metrics, namely the size of the largest component, and the total remaining flow in the system.~~ Our results show that the federal actions have a strong impact on the network, while the local ones usually do not break it before almost all cities are isolated. Choosing the cities with higher degrees for the targeted attacks is the best option in most cases, considering the size of the largest component, especially for the two largest networks ($N = 5420$ and $N = 620$ cities). However, there is a transition, showing that the vulnerability index performs nearly the same as the degree for the São Paulo network and it is the best choice for the network of the Brazilian states ($N = 27$ nodes) under most threshold levels.

~~The presented robustness analysis can be applied in different domains as well, from epidemiological spreading (Santos et al., 2009; Danon et al., 2011), as the main motivation for this paper due to the SARS-CoV-2 pandemic, to the mitigation of extreme events and natural hazards into critical infrastructure networks, such as wildfires in power grids and floods and landslides in highways (Santos et al., 2017, 2019b), or cities whose importance in mobility is vital for the transit of people and supplies. Such mobility-based analysis is important for urban planning as well, for regional development, especially in a continental-dimension country like Brazil~~.

~~In future works, we would like to perform simulations with epidemic models such as the Branching Processes and variations of SIR (susceptible, infected, and removed) (Barabási et al., 2016; Coelho et al., 2020; Cota, 2020) on top of the investigated networks to assess how the attacks help stop the spreading processes.~~

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